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Introduction

Technical change embodied in fishing fleets through the adoption of new technology has markedly contributed to the increased harvesting capacity of fisheries around the world. Over the past few decades, vessel owners have made substantial technical improvements to their boats and equipment to increase yields as well as to enhance safety. Vessels' wood hulls have been replaced with steel over wood or all steel hulls, and the proportion of ferro-cement and fiberglass hulls has expanded. Engines are being built or adapted to be more powerful and efficient. A myriad of electronics have been adopted, such as global positioning systems, route tracers, hydro-acoustic devices, onboard computers, and satellite-based communications. Overall, it has been estimated that global fishing power has increased at an annual rate of 9.0 percent per year through these types of technological improvements (Fitzpatrick 1995).

Studies by the Food and Agriculture Organization (FAO 1997,1998a,b) have established both that the number and catching capability of participants in fisheries world-wide has substantially increased, and that capacity needs to be reduced in virtually all fisheries to move toward a sustainable balance. Garcia and Newton (1997) document that approximately 70 percent of the world's marine capture fisheries are overexploited, fully exploited, or recovering. They also estimate that fishing capacity should be reduced by 53 percent in order for operating revenues to equal the total cost of production. Mace (1997) finds that harvesting capacity in the world's industrial fisheries increased at a rate eight times greater than the rate of growth of landings from world capture fisheries.

Although technical progress has clearly exacerbated this capacity issue by augmenting the capability of operating units to increase harvest levels, no economic studies have attempted to quantify the extent or effects of technical change in fisheries over time. Efforts to evaluate technical progress in fisheries have instead been confined primarily to engineering studies. But information on the economic contribution of investments in fishing technology is crucial for evaluating both the production impact of, and the returns to, such investments. Evidence on the amount of technical change, and its contribution to actual catch and expansion of available fishing power, is central to decisions by vessel owners, as well as fisheries managers concerned with establishing and reducing capacity levels.

Economic measurement of the productive contribution of technical progress is usually based on models representing output growth given inputs (primal), or cost diminution given output (dual), over time. It is therefore measured in the primal context, for example, as output growth net of observed input changes. Such a disembodied technical change notion, motivated by Solow (1957) and providing the basis for the large literature on the Solow productivity residual, has both computation and interpretation limitations that are widely recognized. One issue in particular is that "technical progress" is in this context simply represented as the ratcheting upward of net output over time – related to a time counter – rather than directly associated with technological innovation (Lambert and Shonkwiler 1995)

For most applications, however, this seriously limits the interpretability of the resulting technical progress measures, since all technological, market, or other factors affecting output production or input use, or their measurement, are lumped into the productivity residual. In particular, if one is attempting to determine the returns to investment in specific technologies, or the actual output production (catch) contribution of a particular type of technical advancement for a fishery, a model more directly recognizing the impact of embodied innovation and its components is necesssary.

Construction and implementation of such a model requires data on investments for specific types of technological equipment that are designed to increase the productivity or competitiveness of the individual decision-making-units (vessels). If recognized separately in an econometrically implementable model, the returns to these investments – in the context of production augmentation – can then be distinguished from other external technical change, regulatory, and environmental factors, that would otherwise all be attributed to disembodied technical change. That is, the productivity residual, which captures any adaptations in the operating environment over time that might affect productivity, may be divided into components to facilitate its interpretation.

In this study we use a detailed data set on technological investments and innovations of 19 vessels in the Sete fishing fleet of Southern France over the 1985-99 time period, to identify various components of embodied and disembodied technical change, and their productive contributions to overall catch. We distinguish the contributions from technical change embodied in the capital base (vessels), and the electronic equipment and other technology applied to it through (internal) purchases by vessel owners, separately from disembodied "technical change" that may have arisen from adaptations in (external) technical, regulatory, environmental, and resource stock conditions. We also examine the contribution of technical efficiency to observed output – changes in how close a vessel is operating to its maximum potential catch level, given observed input use. And we evaluate whether output compositional changes affect the productivity and returns measures.

Overall, we find that embodied technical change increased at approximately 1.1 percent per annum for the Sete fleet overall between 1985-99. That is, changes in vessel characteristics (size, hull material, the number of drums, and engine power), and the technological base (such as the adoption of sonar, route-tracers and onboard computers) enhanced production by more than 1 percent per year. Of this, technical change associated with capital (vessel) adaptations increased catchability by an average of 0.46 percent per year. And technical improvements directly due to investment in new technology generated the remaining productivity increase of 0.61 percent per year. Concurrently, external events, such as declines in resource abundance and changes in management or regulations, captured as overall "disembodied technical change", caused a net output decline of approximately 3 percent per year. By contrast, increased effort put forward by the fleet as a whole, which is also associated with reduced resource stocks, augmented catch rates, but by less than 0.1 percent. And neither output composition or efficiency changes appear to have had a substantive effect on productivity.

The Data

The Sete fleet is made up of two types of trawlers, bottom trawlers (the traditional activity), and pelagic trawlers (an activity that increased greatly in the 1980s). Trawlers of both types may change fishing strategy according to market conditions for small pelagics (sardines and anchovies). Most vessels targeted anchovy from 1987 to 1992, but many switched back to traditional demersal species once the market for anchovy became less remunerative.

The main technical developments during the late 1900s included increased size and power of vessels, and development of pelagic trawling in the 1980s and electronic equipment in the 1990s. All Sete trawlers already had some types of electronic equipment at the beginning of the 1980s, including a navigation radio, precision automatic pilot, radar, and radioelectric navigation equipment. But during the past 20 years many types of investments have been made to enhance the technological base. For example, VHF began being used for offshore-onshore communications in the mid-1980s, and GPS was introduced in the early 1990s, followed by onboard computing and the use of sonar.

For our analysis we used data on production activities for 19 vessels in the Sete fleet, operating between 1985 and 1999, and representing a broad range of sizes and output/input patterns. These data, obtained by the Institut du Développement Durable et des Ressources (Montpellier, France), include information on species landings, input characteristics, and technological equipment and investment. We have data on two outputs, whitefish (traditional demersal species) and bluefish (anchovies and sardines), measured by pounds landed.[1] Measured vessel and gear characteristics include gross registered tonnage (GRT), vessel length (LEN), engine horsepower (HWP), hull construction (HULL), number of drums (DRUM), and number of two kinds of nets used (N1-N2). Technology variables include sonar (SON), route tracer (RT), global positioning system (GPS), kort nozzle (NOZ), onboard computers (COMP), and whether or not the vessel had adopted alternative processing activities (PROC).

The oldest vessel (vessel 10) in the fleet was constructed of wood in 1947, is relatively small (26.1 GRT), and as of 1999 had not installed sonar. At the other extreme is vessel 8, which was built in 1994, has a plastic hull, and is the largest vessel (96.66 GRT) in the sample fleet. It was outfitted with sonar, GPS, a route tracer, and an on-board computer. Between these ranges a wide variety of innovative behavior has been exhibited, but during the sample period most of the vessels adopted considerably more modern technology.

Fishery independent measures of resource abundance to use as control variables for resource stock levels, and thus distinguish this aspect of environmental conditions from

[1] Some data on the value of these outputs, and thus implicitly their price (French Francs), was also available. Although these data potentially could be used to reflect changes in the quality of the catch, or choice of species through augmenting the specification by output choice equations (assuming profit maximization), the value data were not sufficiently complete to allow such an extension.

disembodied technical change, were not available. As a proxy for such stock effects, a measure of landings-per-unit-effort—LPUE—was constructed for the entire fleet. LPUE was calculated by summing all vessel landings and days at sea in each year, and then dividing fleet level landings by fleet level fishing effort. $LPUE_{-1}$ (lagged one period) was then used as an indicator for catch per unit effort, potentially capturing some stock abundance effects. This measure is not ideal for such a task, however, so stock effects still likely appear in the productivity residual.

The Methodology

Technical change from an economic perspective involves shifts in the relationship between production (output) and factors of production (e.g., capital, labor, energy, and materials). It is thus typically defined and measured as the percentage change in net output between consecutive time periods, and conceptually motivated as a shift in the production function. Increases in the resulting measure implies declines in the resources (inputs) used to produce a given amount of output. If the associated shift in the production technology affects the use of all inputs equivalently – without affecting their marginal rates of technical substitution – technical change is neutral. If it instead involves a rotation of the underlying production technology, and thus a change in input composition, the underlying technical change is non-neutral (or biased), in turn implying cross-effects with the inputs.

To justify the use of this methodological base for defining and measuring technical change we must have appropriately represented the input base, and the form or determinants of technical progress. That is, technical change must stem from external forces, rather than explicit investment carried out by the firm/vessel owner that would involve an increase in some type of input. If formalized by a production function that expresses output produced (catch), Y, as a function of a vector of inputs used, **X**, this suggests that an external factor, generally expressed as a time counter, t, is recognized as a production determinant: $Y=Y(\mathbf{X},t)$. Disembodied technical change is thus measured simply by changes in output produced, given input use, over time – or $\partial Y/\partial t$, usually expressed in proportional or percentage terms as $\partial \ln Y/\partial t$.

If changes in $Y(\mathbf{X})$ also occur due to identifiable changes in the technological or capital base stemming from purchases by the firm (vessel owner), these endogenous or embodied technical change factors or drivers should be recognized and distinguished by generalizing the representation of the production technology. Such a relationship may be specified according to the production function $Y(\mathbf{X},\mathbf{K},\mathbf{T_E},\mathbf{t_D},\mathbf{S})$, where $\mathbf{X}$ is a vector of variable inputs, $\mathbf{K}$ a vector of capital stocks, $\mathbf{T_E}$ a vector of embodied technological factors, $\mathbf{t_D}$ a vector of disembodied technical change drivers, and $\mathbf{S}$ a vector of environmental conditions affecting production.

More specifically, for our analysis we will define the one component of the $\mathbf{X}$ vector as "days at sea" (or "effort", $X_1=E$). Although this input specification is not typical for production analysis, it is consistent with the way managers and fishery researchers represent fisheries inputs. Effort, proxied by days at sea, reflects energy, materials, and labor inputs applied to the (quasi-fixed) capital stock. This summary measure, sometimes motivated as an intermediate output from the first of two production stages (Pollak and Wales), is used at least in part because more explicit input measures – such as fishermen on board or fuel used – are usually unavailable or vary little on a per-day basis.[2]

A measure of resource abundance, or the resource stock/biomass, could also be incorporated as part of the $\mathbf{X}$ input vector. It alternatively might be thought of as an external factor, and appear in the $\mathbf{t_D}$ vector. However, these treatments disregard the unique characteristic of the resource stock as a "discretionary" input. It is not under the control of any particular vessel or skipper, but it is clearly affected by the decisions of vessel operators in the fleet as a whole, as well as fishery managers.[3] It is also a critical determinant of the environmental climate within which the vessel is operating.

Therefore, we will include our proxy for changes in the resource stock, $LPUE_{-1}=S_1=S$, as the only component of the **S** vector. Distinguishing this "input" into fish production or catch is an attempt to separate stock impacts from disembodied technical change effects, although its effectiveness in doing so depends on the appropriateness of the stock measure.

The **K** components that are individually measured for the Sete fleet consist of capital characteristics for the particular boat. Gross tonnage (K_1), length (K_2), type of hull (1 for wood, K_3), number of drums (1-4, K_4), and number of engine changes (ENGC,1-3, K_5), are represented. We are implicitly assuming, when defining these characteristics as inputs, that each has a positive marginal product that reflects a component of embodied technical change derived from capital investment.[4] This might not be true, however, for some vessel characteristics. For example, greater length could potentially imply an older more cumbersome boat, which might be reflected in a negative marginal product estimate.

The embodied technical change variables we employ as components of the $\mathbf{T_E}$ vector could also be thought of as capital stock components. But it is useful for our purposes to distinguish them separately from vessel characteristics to facilitate interpretation of the resulting measures. For this data set our $\mathbf{T_E}$ variables are variable pitch propeller, T_1, kort nozzle, T_2,

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[2] This type of analysis could also focus on explaining catch/day rather than catch (output, Y). However, including days (effort, E) as an argument of the function controls for days within the estimating model without the implicit assumption that its coefficient is 1.

[3] An individual skipper also has options about where to fish, which will affect the effective stock level for the particular boat, although characterizing such a vessel-specific measure it not possible with these data.

[4] Note that any of these variables that are constant for a given vessel – GRT, length, and type of hull in particular – will not show up in a technical change computation for a particular vessel or for the fleet overall, since they do not change over time.

sonar, T_3, netsonde, T_4, GPS, T_5, route tracer, T_6, computer, T_7, and processing facilities (amelioration of processing and storage), T_8. Increases in these factors are again assumed to be productivity-enhancing, or have a positive marginal product, thus generating upward shifts in the production frontier that can be attributed to (embodied) technological asset investment.

We include only one explicit "disembodied technical change" factor $\mathbf{t_D}$; t_1=t is a time counter, representing shifts in the production function each year. The output change associated with changes in t lumps any trends in output productivity, or shifts over time not explained elsewhere in the specification of the production or technical relationship, into the overall technical change or productivity measure. In this sense it is, as Solow noted, a "measure of our ignorance". However, when included in a model that explicitly recognizes – and thus allows for the explanatory power of – embodied technical change investment, this measure captures the impacts only of other uncontrolled-for factors. This might in the current context include un- or mis-measured changes in the biomass stock, or the number of vessels participating in the fishery, that reduce (or enhance) the productivity of an individual vessel independently of the amount of technology, capital, fishermen, and other inputs devoted to the productive process.

We also consider two adaptations to this overall framework representing production processes and thus productivity patterns. First, note that the typical characterization of the production technology in the form of a production function presupposes that output composition changes are not an important part of the puzzle. However, in a multi-output industry, or fishery, this assumption may be inappropriate. One way to deal with this is to define instead a distance function, as discussed in Coelli et al (1998). We will just briefly summarize this framework here, since it does not comprise a substantive part of our analysis; recognizing multiple outputs turns out empirically not to be a key issue for our application.

A distance function (output-oriented) may be thought of as a multiple output production function allowing for deviations from the production frontier, or technical inefficiency.[5] Such a function may be defined as $D_O(\mathbf{X,Y,R}) = \min\{\Theta: (\mathbf{Y}/\Theta) \quad P(\mathbf{X,R})\}$, where $P(\mathbf{X},\mathbf{R})$ is the production set generally defining the production technology, and the **R** vector includes any production determinants not appearing in the specified output (**Y**) and input (**X**) vectors. If $D_O=1$, and $Y=Y_1$ is the only output, this collapses to a standard production function. If $D_O=1$ and there are multiple outputs, it may be interpreted as a multi-output production function. In turn, if $D_O \neq 1$, the distance function recognizes a one-sided "inefficiency error" in addition to the standard white noise error appended to estimating equations for standard econometric models, which may be estimated using stochastic production frontier (SPF) methods.

This raises our second adaptation – recognizing technical inefficiency by allowing for such a two-component error term in either the distance or production function model. This facilitates consideration of whether observed output increases – enhanced productivity – imply that firms (vessels) are expanding their technological horizons (shifting the production frontier out), or moving toward an existing frontier.

That is, the usual production function framework is only representative if the boats are operating efficiently in each time period – they are on the technological frontier, so any change in **Y** given other arguments of the function can be interpreted as a shift of the frontier. If, however, some boats are operating within the frontier, due to some type of unexplained inefficiency (skipper skill, for example), it is possible also to increase **Y**/**X** by moving toward the frontier. Such efficiency adaptations can be identified if deviations from the frontier are allowed for in the estimation of the production relationship.

[5] See Paul (1999) for a brief introductory discussion of these issues, and Coelli et al. (1998) for a more

The Measurement of Technical Progress

In order to empirically identify the independent impacts of each determinant of the $Y(E,\mathbf{K},\mathbf{T_E},t,S)$ frontier on production (catch), and ultimately the overall implications for technical progress, we need to quantify these impacts. This requires assuming functional forms for the production (or distance) function, and for the statistical error term (or terms), and estimating the parameters of $Y(\cdot)$.

Assumptions about the functional form for $Y(\cdot)$ necessary for econometric implementation are sometimes thought to be limiting, although if the data suggest more complex relationships exist this can be accommodated. In particular, a standard approximation to the production function is a first-order log-linear or Cobb-Douglas (CD) functional form:

1) $\ln Y_{it} = \alpha + \beta_E \ln E_{it} + \Sigma_k \gamma_{Kk} \ln K_{k,\,it} + \Sigma_j \delta_{Tj} T_{j,it} + \alpha_t t + \beta_S \ln S_t + v_{it}$,

where k denotes the capital inputs, j the technological innovations, E, S, and t are defined as above, and v_{it} is an error term (assumed to be independently and identically normally distributed), representing "white noise" in the data. The panel-nature of the model with I boats (denoted i) and T time periods (denoted t), is also explicitly represented in (1), although we suppress these superscripts for notational simplicity in most of our treatment. This functional representation may easily be extended into a second-order (translog) approximation, allowing a full range of curvature possibilities to be reflected in the output-input relationships, by adding second-order (cross and squared) terms among the arguments of the function.[6]

When a number of the arguments are qualitative variables (in a restricted range, such as 0-1, HULL, or 0-4, DRUM), however, the extra information provided by such cross-terms might be limited. That is, in general these factors might be thought to not only shift but also twist the

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complete overview of and references for frontier analysis.

function (be non-neutral), but the additional rotation might not be well defined when measurement is based on qualitative information.

For our analysis we initially incorporated a full range of 2^{nd}-order terms in (1), but found that they were largely uninformative. Even the few cross terms that were statistically significant, and thus remained the model for the production function (p.f.) framework, became insignificant for the multiple output (distance function, d.f.) specification. The somewhat more general form of model (1) we use for estimation,[7]

$$2) \quad \ln Y_{it} = \alpha + \Sigma_i \lambda_i DUM_i + \beta_E \ln E_{it} + \Sigma_m \beta_{mE} V_{m,it} \ln E_{it} + \Sigma_k \gamma_{Kk} \ln K_{k,it}$$
$$+ \Sigma_j \delta_{Tj} T_{j,it} + \alpha_t t + \beta_S \ln S_t + \Sigma_m \beta_{mS} V_{m,it} \ln S_t + \beta_O O_{it} + \Sigma_n \beta_{Nn} N_{n,it} + v_{it},$$

thus allows for cross-terms with ln E and ln S (where V_m may be any argument of the $Y(\cdot)$ function), and fixed effects (dummy variables) for each boat. This specification also includes variables representing supplemental information on the operating scenario of the vessel – changes in boat ownership (O) and number of nets of type 1 and 2 (net otter trawls and mid-water trawls, N_1 and N_2) – which exhibited statistically significant estimated contributions in preliminary empirical investigation.[8]

Estimates of the parameters of (2) are typically interpreted as representing the contributions of each factor to overall production, or their "returns". For example, $\partial \ln Y/\partial \ln E = \beta_E + \Sigma_m \beta_{mE} V_m$ is a proportional expression of the marginal product of E (MP_E), $\partial Y/\partial E \cdot E/Y = MP_E \cdot E/Y$, or the output elasticity $\varepsilon_{YE} = \partial \ln Y/\partial \ln E$. To estimate the actual productivity impacts corresponding to the various types of technological innovations captured in our data, and

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[6] If all such terms are included the resulting function is a fully flexible translog function.
[7] For implementation of the distance function framework, as elaborated below, the left hand side of equation (2) is specified as ln Y_1, where Y_1 is whitefish, and the output ratio $Y_{RAT}=Y_2/Y_1$, where Y_2 is bluefish, appears on the right hand side. A squared Y_{RAT} term also was kept in the function due to its statistical significance.

combine them to generate an overall measure of technical change, we can take this one step further. This step is analogous to that used to motivate the Solow residual, extended to recognize the various driving factors for productivity growth embodied in our framework.

First, note that the observed change in output between two time periods can analytically be expressed as the total derivative dY/dt, so taking this derivative decomposes the full change into the individual factors driving it:

3) $dY/dt = \partial Y/\partial E \; dE/dt + \Sigma_k \partial Y/\partial K_k \; dK_k/dt + \Sigma_j \; \partial Y/\partial T_j \; dT_j/dt + \partial Y/\partial S \; dS/dt + \partial Y/\partial t$,[9]

or, in proportionate or percentage terms,

4) $d\ln Y/dt = \partial \ln Y/\partial \ln E \; d\ln E/dt + \Sigma_k \; \partial \ln Y/\partial \ln K_k \; d\ln K_k/dt + \Sigma_j \; \partial \ln Y/\partial T_j \; dT_j/dt$

$+ \; \partial \ln Y/\partial \ln S \; d\ln S/dt + \partial \ln Y/\partial t$,

where logarithmic derivatives are taken for continuous variables (such as E) and level derivatives for variables that are in the form of qualitative variables or "counters" (0-1 variables or time).

Note that qualitative variables – such as the dT_j/dt terms – will fall out of this computation for most observations. That is, such a derivative represents the change in the variable between two time periods. Therefore, the only time a 0-1 dummy variable would show up in expression (4) would be in the period the shift actually occurred. Similarly, if any variable (such as GRT) does not change within the sample (for a particular time series – a boat in our analysis), it will drop out of this expression.

In a nonparametric framework (based on just data manipulation without estimating the relationships), a technical change or productivity residual representing the output change not explained by the inputs in the **X**, **S**, **K** and $\mathbf{T_E}$ vectors could be imputed by rewriting (4) as:

[8] Some linear dependency occurred between the boat dummy variables and the 0-1 technology variables, so dummies for boats 17, 23 and 27 were dropped from the estimation.

$$5)\quad \partial \ln Y/\partial t = d\ln Y/dt - \partial \ln Y/\partial \ln E \; d\ln E/dt - \Sigma_k \, \partial \ln Y/\partial \ln K_k \; d\ln K_k/dt - \partial \ln Y/\partial \ln S \; d\ln S/dt$$

$$- \Sigma_j \, \partial \ln Y/\partial T_j \; dT_j/dt \; ,$$

where the derivatives such as dln Y/dt are computed as percentage changes from the data (dln Y/dt is the percentage change in output between periods t_0=1984 and t_1=1985, or ln Y_{1985}-ln Y_{1984}, for example), and the elasticities such as $\varepsilon_{YE} = \partial \ln Y/\partial \ln E$, that weight these changes, are approximated by input shares, assuming profit maximization.[10]

However, for some arguments of the function (probably all for our application), an appropriate price may not be available to compute an input share, or the profit maximizing assumption may be inappropriate. We then wish to attribute the factor's true contribution without assuming the firm/boat owner has already provided this information implicitly by making choices balancing the marginal costs of an action by its marginal benefits.

To do this, we measure the effective contribution of the inputs to output through parametric estimation of the elasticities $\partial \ln Y/\partial \ln E = \varepsilon_{YE}$, $\partial \ln Y/\partial \ln K_k = \varepsilon_{YKk}$, $\partial \ln Y/\partial T_j = \varepsilon_{YTj}$, $\partial \ln Y/\partial \ln S = \varepsilon_{YS,}$ and $\partial \ln Y/\partial t = \varepsilon_{Yt}$, and weight them by the actual changes in the associated arguments of the function, to compute the components of (4).[11] We can then average these measures over boats and/or years to determine overall patterns for the fleet as a whole.

[9] For simplicity we will leave the contribution of the addition variables added to the analysis, O and N_n, out of these specifications, although strictly speaking they should be included since they are arguments of the production function.

[10] If profit maximization is assumed, and prices for each input observable, the profit maximization condition is $VMP_m = MP_m \cdot p_Y = p_m$, where $MP_{im} = \partial Y/\partial X_m$ is the marginal product of input X_m, p_m the price of X_m, p_Y the price of Y, and VMP_m the value of the marginal product. Thus $MP_m = p_m/p_Y$, so $\varepsilon_{YXm} = p_m X_m/p_Y Y$ – the revenue share – which can be computed directly from the data.

[11] In this parametric framework $\partial \ln Y/\partial t$ is directly estimated, rather than solved out in residual form as in (5). This implies, however, that a residual remains for equation (4) that is comprised of all unmeasured or uncontrolled for factors that drive the errors in estimating the true relationship.

In turn, we can isolate and analyze specific pieces of the production and technical change puzzle captured in (4). First, note that the impacts of various types of technical changes are reflected in the final components of (4), associated with the T_j and K_k factors and t:

6) $TECH_{E,D} = \Sigma_k \partial \ln Y/\partial \ln K_k \, d\ln K_k/dt + \Sigma_j \partial \ln Y/\partial T_j \, dT_j/dt + \partial \ln Y/\partial t$,

where the E,D subscripts indicate that both embodied ($\mathbf{K}$, $\mathbf{T_E}$) and disembodied (t) factors are included. The first element of this expression is technical change embodied in capital: $TECH_K = \Sigma_k \partial \ln Y/\partial \ln K_k \, d\ln K_k/dt = \Sigma_k \varepsilon_{YKk} \, d\ln K_k/dt$. The second is technical change embodied in the technological base: $TECH_T = \Sigma_j \partial \ln Y/\partial T_j \, dT_j/dt = \Sigma_j \varepsilon_{YTj} \, d\ln T_j/dt$.[12] A combination of these indicators thus reflects embodied technical change impacts: $TECH_E = TECH_K + TECH_T$.

The third piece, $TECH_D = \partial \ln Y/\partial t = \varepsilon_{Yt}$, that captures the remaining (unexplained) output trends, is typically interpreted as disembodied technical change. But, as alluded to above, the value of $TECH_D$ can also be driven by anything else that is changing over time, such as regulations, biomass stock adaptations not captured in the S measure, or other types of stress/impacts on the fishery. It is particularly likely in the fisheries context that $TECH_D$ reflects something other than technical change, since there are so many unobserved and uncontrollable factors not captured in the specified production function (especially at the boat level).

Finally, one measure that could be computed to shed some light on these additional factors would be an analogous "technical change" measure representing the impacts of external environmental or stock changes rather than technical change directly. This would be computed analogously to those for the more specific technology factors as $TECH_S = \varepsilon_{YS} \, d\ln S/dt$, which represents the productive contribution of S adaptations.

[12] It should be emphasized that these components reflect both the actual technological investments made ($d\ln K_k/dt$ and dT_j/dt), and their corresponding contributions to output production ($\varepsilon_{YKk} = \partial \ln Y/\partial \ln K_k$, $\varepsilon_{YTj} = \partial \ln Y/\partial T_j$).

The Results: elasticities and technical change components

Estimation of the model represented by equation (2), to measure the components of (4), can be carried out by ordinary least squares (OLS), since even with cross-terms the function remains linear in the parameters. Such estimation is based on the maintained assumption that the error term v_{it} is normally distributed. Various econometric adaptations to the model can be made to accommodate possible deviations from this simple stochastic assumption, such as heteroskedasticity or autocorrelation. However, these proved unimportant for our specification, according to standard tests.

The model may also be adapted to recognize the potential presence of technical inefficiency, by assuming a two-part error term of the form $\mu_{it} = v_{it} + u_{it}$. This combines the symmetric (white noise) error term v_{it} with an asymmetric or one-sided (inefficiency) error term, u_{it}, that reflects the productivity contributions of changes in efficiency (estimated deviations from the production frontier). Such a function may be written as

7) $\ln Y_{it} = \ln Y_{it}(DUM_i,E_{it},K_{k,it},T_{j,it},t,S_t,O_{it},N_{n,it};\alpha,\beta,\gamma,\delta) + v_{it} + u_{it}$,

where $\ln Y_{it}(DUM_i,E_{it},K_{k,it},T_{j,it},t,S_t,O_{it},N_{n,it};\alpha,\beta,\gamma,\delta) + v_{it}$ represents equation (2).

The adaptation to multiple outputs, by specifying a distance function, is in turn a simple extension of this function. First, the distance function mentioned in the previous section may be written (as developed in depth by Coelli et al.), as

8a) $\ln D_{O,it} = \ln Y_{it}(DUM_i,E_{it},K_{k,it},T_{j,it},t,S_t,O_{it},N_{n,it};\alpha,\beta,\gamma,\delta) + \eta_1 \ln Y_{1,it} + \eta_2 \ln Y_{2,it}$

$+ \Sigma_{rs}\, \eta_{rs} \ln Y_{r,it} \ln Y_{s,it} + v_{it}$

to accommodate the two outputs Y_1 and Y_2 (r=1,2).[13] Certain regularity conditions, in particular homogeneity of degree one in outputs, must theoretically hold for this function. As in Lovell et al. (1994), however, these conditions can be simply imposed by normalizing the function by one of the outputs, resulting (for our two-output specification) in:

8b) $\ln D_{Oit}/Y_{1it} = \ln Y_{it}(DUM_i,E_{it},K_{k,it},T_{j,it},t,S_t,O_{it},N_{n,it};\alpha,\beta,\gamma,\delta)+ \eta_2 \ln Y^*_{2,it}$

$+ \eta_{22} \ln Y^*_{2,it}{}^2 + v_{it}$, or

8c) $\ln Y_{1it} = -\ln Y_{it}(DUM_i,E_{it},K_{k,it},T_{j,it},t,S_t,O_{it},N_{n,it};\alpha,\beta,\gamma,\delta)- \eta_2 \ln Y^*_{2,it}$

$- \eta_{22} \ln Y^*_{2,it}{}^2 - v_{it} + u_{it}$,

where $Y^*_2=Y_2/Y_1$, and $u_{it}=\ln D_{Oit}$ is the one-sided "inefficiency" error, which equals zero if $D_{Oit}=1$ so the firm (vessel) is on the frontier of the function. This is the maintained hypothesis for the reported preferred version of this alternative model in our empirical results, since inefficiency contributions to explaining productivity change appear negligible for these data.

In this section we present estimates for three specifications, corresponding to equations (2) (standard econometric production function model – the base specification), (7) (stochastic production function frontier, SPF, model), and (8c) with $u_{it}= 0$ (standard econometric distance function model). The arguments of the functions include E and S, five **K** components (K_1=GRT, K_2=LEN, K_3=HULL, K_4=DRUM and K_5=ENGC), eight $\mathbf{T_E}$ variables (T_1=PROP, T_2=NOZ, T_3=SON, T_4=NSOND, T_5=GPS, T_6=RT, T_7=COMP, and T_8=PROC), boat dummies (DUM_i), O, N1 and N2. In the two-output model Y_1=whitefish and Y_2=bluefish are separated. The preferred specifications for each model were chosen by initially including a full set of dummy variables and cross terms, and then deleting those that were insignificant or redundant. Estimation of the

[13] For flexibility of the function cross-terms between the outputs and the arguments of the $Y_{it}(\cdot)$ function would also be included. These terms are omitted here for simplicity, as well as because they were

standard econometric models was carried out by PC-TSP (Hall, Cummins and Schnake, 1996). Estimates for the stochastic frontier models were generated using FRONTIER (Coelli, 1996).

First consider the data patterns evident from the averages of changes in the data – output(s), and the arguments of $Y(\cdot)$ – for the entire sample, presented in Table 1. All technical change (T_j and K_k) factors have increased over time. This represents the direct incidence of changes in technology – the innovations that were actually put in place over this period. For example, the average yearly increase in the use of T_2 (NOZ) for the entire fleet over the 1985-1999 period was 4.3 percent.

This compares to an average increase in output of only 0.33 percent, and in fact apparent declines in each of the individual outputs. The seeming inconsistency is due to the very high variation in the catch of Y_2 (bluefish), which had dramatic down- as well as up-swings, the former appearing more in the 1994-99 time period (and dominating), and the latter in the 1985-93 period. Note also the very different time trends for the (small) overall increases in fishing effort and resource abundance; E growth was negative on average in the first half of our data sample and positive in the second half, and the reverse pattern was evident for S.

Given the patterns exhibited in the data, it is worth emphasizing that falling stocks, or stress on the fishery – as suggested by the measured changes in E and in S ($LPUE_{-1}$) – will reduce the impacts of technical change on catch levels, especially for a particular boat. Due to such external factors boats might ultimately fail to maintain the status quo, much less enhance output, even with significant technological investment. Since individual boats are competing for fish, a catch-up game is implied. Technological investments that would have an impact if others did not change their procedures may just allow boats to retain their share if something like a

invariably insignificant in preliminary empirical investigation and thus were not included for empirical implementation of the distance function.

zero-sum game is taking place. Such a scenario is suggested by the fact that investment in technological improvements far exceeds the associated negligible change in output production.

The *economic* contributions of the technical changes evident from the K_k and T_j adaptations must be expressed in terms of their actual impact on production, balanced by changes in other inputs and environmental conditions. Determining the productive contributions of individual innovations to production first requires evaluating the estimated parameters of the model, representing the returns to technological investments.

The parameters of the model were first estimated by applying OLS to the CD production function (1), to determine overall patterns. The resulting returns to effort measure, $\varepsilon_{YE}=\beta_E$, was positive and significant, and that for stock, $\varepsilon_{YS}=\beta_S$ negative and significant. This is consistent with *a priori* expectations of a positive marginal product for E and a negative relationship between increased catch in the previous year ($LPUE_{-1}$) and current stock abundance. However, some of the other results suggested interpretation difficulties, many of which remain in the more complete representations including cross effects.

The parameters on the K variables, $\varepsilon_{Yk}=\gamma_{Kk}$, implied negative marginal products for three of the five capital components, with those for K_1 and K_2 significantly negative. And the $\varepsilon_{Yj}=\delta_{Tj}$ coefficients representing the productive contributions of embodied technological innovations were positive on balance, but also captured some negative impacts. In particular, the coefficients on T_1 and T_5 were significantly negative, and those for T_2 and T_6 insignificantly negative. Also, the trend effect reflected by $\varepsilon_{Yt}=\alpha_t$ was strongly negative (indicating a depressing effect on productivity of the fishery over time, holding all else constant).

The most difficult to interpret implication was the (almost invariably significant across a variety of specifications) negative contribution of T_5 (GPS). One possible explanation is that

GPS adoption was associated with some other types of unmeasured output-dampening impacts, such as stock or regulation changes, that are being picked up as part of the GPS-effect. This is particularly likely given the evidence of a significant fall in output production in 1993. Since this is around the time GPS was being adopted, the drop may appear to be GPS-driven, and yet actually be attributable to something else that is unmeasured. The negative relationship could also be due to GPS being superceded (or at least closely followed) by the introduction of computers and sonar. So, relative to other boats, GPS alone may indicate depressed technical innovation. Another possibility is that some type of underlying time dependence relates GPS with the error term, which is suggested by the fact that the only real impact of autocorrelation adjustments on this model was to make the statistical significance of this variable negligible.[14]

The driving forces for other discrepancies of parameter estimates from their expected signs were also scrutinized for intuitive explanations. And interactive effects were tested for by incorporating cross-terms with other variables in the estimating function. But few linkages were found to be substantive, so little explanatory power from biases was evident. The (insignificant) coefficient on T_2 (NOZ) seems attributable instead to the fact that it is a fuel-saving device, and since fuel inputs are not represented here T_2 does not contribute to production net of input use. And the estimates for the coefficients on the T_7 (COMP) and K_4 (DRUM) variables were so insignificant and small in magnitude that they have virtually no estimable effect on output production, and so were left in the analysis only to illustrate this negligible impact.

Such insignificance could be at least partly due to linkages with other technological variables that are absorbing the independent impacts of these innovations. For example the

[14] Although the existence of autocorrelation was suggested by this adaptation, little substantive difference in other estimates was established, so to maintain comparability with the stochastic production frontier estimation used for comparison the model was not adjusted for autocorrelation. Note, however, that the

effect of computers could be imbedded in the estimates for the impacts of route-tracers or processing facilities, since they seem to some extent to be joint purchases. If T_8 is not included in the estimation, the impact of T_7 appears significant and larger, suggesting a temporal combination of innovations. Similar forms of jointness may contribute to the apparent negligible impact of investments in the capital base, **K**. These types of inter-connections are difficult, however, to establish quantitatively with qualitative or boat-specific data. Importantly, however, although such linkages may convolute the implied significance of any one measure, the combined measures are much more robust and thus definitive.

Although most cross-terms incorporated in these models turned out to be uninformative, the few which are significant, as documented in the Appendix Tables A1a-c, provide some useful insights. The final models for the production function (p.f.) specifications include cross terms between S and T_4, K_1, K_2, and N_2, and between E and T_5 and T_6. But for the distance function specification the interactions with the **T** variables and with N_2 were very insignificant, and thus were deleted.[15] The only additional significant terms for this specification were 1st-order and squared terms for Y^*_2 (with Y_1 instead of Y as the dependent variable).

The significance of the δ_{T4S} and δ_{T4S} terms indicates that the contributions of T_4 (NSOND) and T_6 (RT) decrease with S levels and E levels, respectively, and that the negative impact of T_5 (GPS) becomes less so at higher E levels. In fact, the contribution of T_6 appears strongly positive in the 1st-order when the 2nd-order interaction with E is recognized.[16] Also, the results show that the 1st-order impact of greater K_1 (GRT) is to augment output, but the impact is

standard errors used to establish statistical significance are robust to heterskedasticity (robust-White), although this adaptation also made little difference to the implied significance of parameters.

[15] The cross-terms between the **K** components and S were also insignificant, but less so than the others, and so were retained for comparison. They make very little difference to the technical change measures.

[16] T_1 (PROP) also has a positive interaction with E if T_5 and T_6 interactions are ignored. Otherwise it is very insignificant, again suggesting some form of jointness that is not easily represented with these data.

reduced at higher S levels, whereas the reverse is true for K_2 (LEN). These impacts are analogous in sign, but insignificant, for the multiple-output specification, suggesting that these interactions are to some extent related to or explained by output composition.

To evaluate the overall productive force of technical innovations, the output elasticities representing the weights in (4) (for the most part equal to the coefficient estimates due to the lack of significance of second order relationships) must be combined with the actual changes in the data from Table 1.[17] That is, as developed above, the collective impact of the potential productive contributions and the actual incidence of innovation – investment in technology – provides us our overall measures of technical change $TECH_D$, $TECH_K$, and $TECH_T$. These measures, averaged over the entire fleet for the 1985-99 time period, and divided into the 1985-93 and 1994-99 sub-periods, are summarized in Table 2 for our three alternative models.

The estimates for the base model, the p.f. standard econometric framework, show that the effective impact of embodied technical change on output production ($TECH_E$) was an expansion of catchability at an average annual rate of 1.1 percent for all boats in the fleet over the whole time period. However, this yearly growth rate nearly doubled between the first and second sub-periods. This pattern is attributable to lower impacts of technological innovation ($TECH_T$) in the first part of the sample period, since the capital-oriented component ($TECH_K$) is virtually the same in the two sub-periods. The disembodied component of "technical change" was strongly negative, and since $TECH_D=\varepsilon_{Yt}$ just depends on the coefficient estimate α_t it does not vary by sub-sample (the average change in t across the sample is simply 1).

[17] Note that the be estimate of about 1.3 may be interpreted loosely as an indicator of scale economics; since this exceeds 1 it implies that output increases may be generated by a less than proportional increase in the "input" of days, since E is our primary input proxy. However, since the true input base is not measured with accuracy, this interpretation is not at all definitive.

An additional measure included in the table to facilitate interpretation of the disembodied technical change measure is $TECH_S = \varepsilon_{YS}$ dlnS/dt, which represents the contribution of stock effects captured by our (limited) abundance measure, S= $LPUE_{-1}$. The overall impact of increased S on output production or catch appears to be positive (including the interaction effects with **T** and **K**), but it becomes negative by the mid-1990s (for all specifications, but with a smaller magnitude in the two-output model). Although this measure may be interpreted as a resource stock effect, it probably does not effectively accommodate abundance impacts so they are likely also reflected in the negative $TECH_D$ measure.

If the estimating model allows for efficiency changes, by using stochastic frontier maximum likelihood techniques (the p.f. SPF specification), adaptations to the estimated parameters are minor, and changes in the technical progress implications are not substantive. The differences primarily emerge as smaller or more negative marginal products for the **K** variables, as reflected in the negative $TECH_K$ component of $TECH_E$. Although $TECH_T$ is higher in the SPF model, with an upturn over time (but not as dramatic for this case), the combined effect is a smaller total embodied technical change effect ($TECH_E$) of about 0.7 percent.

The productive contribution of efficiency improvements is also minimal, ranging from -0.3 percent (decreasing efficiency) in the first period to less than 0.1 percent (but positive) in the second time period. The lower levels of embodied ($TECH_E$) and efficiency (EFFIC) contributions to productivity are, however, counteracted to some extent by the smaller negative disembodied technical change term $TECH_D$. That is, some of the productive negativity is absorbed in this model by the efficiency and capital contribution trends.

Lower measured productive contribution of **K** changes, and greater impact of **T** changes, also appear in the multiple output (standard econometric distance function) specification. But again, on balance, the implications about the overall output augmentation from technical factors – or innovation – are very similar. In particular, $TECH_E$ is about 0.011 and $TECH_D$ is -0.032, which differ from the p.f. model only at the fourth decimal point. However, the $\mathbf{T_E}$ and **K** embodied contributions have a somewhat different balance, with $TECH_K$ picking up virtually none of the impact; all is attributed to variables in the $\mathbf{T_E}$ vector.

Our technical change measures may also be computed by boat, and by individual time period.[18] We present results for these sub-samples only for the base specification, the standard econometric p.f. model, since the model adaptations do not have significant impacts on the overall technical change story.

Differences across years may be assessed from the measures presented in Table 3, averaged for all boats in the fleet for each year in the sample. The very worst year in terms of regress in the contribution of technological innovations ($TECH_T$) appears to have been 1993-94, at -3.5 percent (with 1995-96 and 1989-90 following), whereas the best was 1997-98, with 1996-97 close behind. In fact the 1990s seem to have been somewhat of a roller-coaster. By contrast to these measures, which were negative for a number of years, returns to capital investment were positive and relatively smooth, reaching as low as zero (or 0.1 percent for those years where some capital investment did occur) to 1.3 percent in 1992-93. The combined embodied effects of these **T** and **K** technological investments, as exhibited by $TECH_E$, was thus driven by the $TECH_T$ patterns.[19] Since the $TECH_D$ measure does not vary for sub-samples, however – it is just an average trend over time – any "disembodied" effects that may have been experienced for a particular year, say, from regulatory or stock impacts, will be reflected in $TECH_E$.

[18] $TECH_D$ is not included in these tables since it is constant for the fleet for all periods.
[19] These time-specific patterns, and also the boat-level measures, were much more dependent on the cross-terms included in the models than were the overall results.

It is also evident from the measures presented in Table 4 that there is quite a substantive variation in the contributions of technological innovation by boat. The greatest contributions from the entire set of embodied technical change factors over the whole sample are, for example, from boats 3, 2, and 13 (in that order), which all exhibited overall technical change advances ($TECH_E$) in excess of 3 percent per annum. By contrast, a number of boats seemed to have experienced negative output contributions from their technical investments, with the decline for Boat 19 reaching nearly 2 percent/year.

This decline is far greater than that apparent for boat 17 (at about -0.2 percent), which might *a-priori* be considered a base case due to its evident lack of technological innovation. However, since these measures are specified in terms of changes rather than levels, for a boat that carried out no innovative behavior – whether from a low or high initial base – $TECH_E$=0. This also suggests why perhaps the most low-tech vessel in this fleet, Boat 10, exhibited only a small productivity decline (all in the first period), whereas the most high-tech vessel, Boat 8, shows only a 1.8 percent increase (all in the second period).

Concluding Remarks

A broad range of conclusions about technical change, productivity, and efficiency of the Sete Trawl Fleet can be reached from the measures presented here. Overall, it appears that technical innovation generated much less effective (output-augmenting) gains than implied by its direct investment, with an average productive impact of embodied technical change ($TECH_E$) of slightly more than 1 percent/year. The disembodied impact on output growth ($TECH_D$) by contrast implies an overall productivity decline of nearly 3 percent/year, which may be attributable to other regulatory, stock, and stress factors in the fishery that counteracted the potential impacts of technological innovations.

The estimated balance of the direct technological factors ($TECH_T$), as compared to those associated with the capital stock ($TECH_K$), in the embodied technical change component $TECH_E$ varies somewhat depending on whether the potential for efficiency gains, or the impact of output composition, are taken into account. If either inefficiency or multiple outputs are allowed for, slightly less productivity enhancement seems attributable to capital-related technical investment. And efficiency changes seem to have had little productive effect.

These conclusions are representative of the results generated by investigation of a wide range of empirical specifications of production and productivity for these data. However, many issues can convolute the estimation and interpretation of technical change and its productive impact in the fishery. Thus these results should not be taken as definitive in an absolute sense, but instead as indicators of relative impacts.

In particular, evaluation of technical and efficiency change fundamentally relies on the appropriate specification of outputs and inputs, and environmental factors and characteristics. However, as is typical for analysis of fisheries, we do not have information on inputs such as fuel, and other inputs (such as the primary effort and particularly resource stock variables) may only be proxied. And, regulatory impacts captured in these estimates are difficult to untangle from the trend ($TECH_D$) and yearly ($TECH_E$) measures.

Also, it is not clear what capital characteristics such as GRT might actually represent in terms of production processes and change (increasing size seems an important aspect of technical development, and yet is not well measured by this or other variables contained in the data). Or what the role of characteristics that essentially are missing – but may be key factors, like horsepower – might be.[20]

[20] The horsepower data were not used since they seem uninformative, and are unreliable. Other proxies for power, such as net length and opening size, could potentially be used but are also unavailable.

Interactions among the technological inputs could also generate misleading results. For example, including “amelioration of processing” (T_8) reduces the measured positive impact of computers (T_7), and the implied negative productivity of kort nozzles (T_2). Such patterns suggest some form of jointness that may not be measured using our essentially qualitative variables, which do not embody sufficient information to capture a broad range of cross-effects. The combined effects therefore are more definitive than each individually.

Given these qualifications, however, our results present an overall picture of ongoing technological innovation and investment to enhance catchability, that has been counteracted by competition among boats, and exogenous forces that are imposing downward pressure on the productivity of vessels in this fleet. Investment in technological innovation thus seems for the fleet as a whole to be largely a game of catch-up, although the results have varied dramatically by boat and time period.

These patterns may also have implications for vessel owners and fisheries management. They suggest for vessel owners that some combinations of investments may “pay” more than others. And that although such investments will not likely enhance overall catch very much, if they are not carried out competitiveness will be sacrificed. Overall, therefore, many resources are being wasted. For the fisheries manager, this suggests that enhancing efficiency involves attempting to adapt incentives for fishermen to minimize this catch-up game, given current concerns about *reducing* catch, particularly with the higher E and lower S levels over time observed in the data.

Implications also arise that support the recent considerable concern exhibited by national and international organizations about capacity issues. Although output production has not increased much as a result of advancing technical innovations embodied in fishing vessels, the potential for catching fish – or capacity – has clearly been enhanced. For example boat 8, which is the most high-tech of the fleet, has the greatest potential catch/day of all the boats – nearly 90 percent more than average. Whereas the catch rates for boats 10 and 17, which are relatively low tech and not very innovative, are only 20-25 percent of the average for the fleet. This suggests that capacity problems are rapidly being exacerbated by this game of catch-up, which must be recognized both for guiding policy with regard to technological innovations, and also for measuring and attempting to reduce excess capacity in fisheries.

Table 1. Output, Input, and Technical Changes:
Means and Standard Deviations, entire and sub-time periods

Change with respect to time	1985-99		1985-93		1994-99	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Total Landings (Y)	**0.0033**	0.496	**-0.0282**	0.520	**0.0422**	0.464
White Fish (Y_1)	**-0.0125**	0.514	**-0.1156**	0.527	**0.1150**	0.469
Blue Fish (Y_2)	**-0.1622**	3.303	**0.2444**	3.138	**-0.6650**	3.444
Fishing Effort, E	**0.0054**	0.365	**-0.0318**	0.390	**0.0513**	0.328
Resource Abundance, S ($LPUE_{-1}$)	**0.0102**	0.164	**0.0353**	0.207	**-0.0208**	0.072
Number of Drums (DRUM, K_4)	**0.0431**	0.239	**0.0709**	0.308	**0.0088**	0.094
Number of Engine Changes (ENGC, K_5)	**0.1412**	0.349	**0.1560**	0.364	**0.1228**	0.330
Variable pitch propeller (PROP, T_1)	**0.0157**	0.124	**0**	0	**0.0351**	0.185
Kort Nozzle (NOZ,T_2)	**0.0431**	0.204	**0.0355**	0.186	**0.0526**	0.224
Sonar (SON,T_3)	**0.0353**	0.185	**0**	0	**0.0789**	0.271
Netsonde (NSOND, T_4)	**0.0314**	0.175	**0.0355**	0.186	**0.0263**	0.161
Global Positioning System (GPS, T_5)	**0.0667**	0.250	**0.0496**	0.218	**0.0877**	0.284
Route Tracer (RT, T_6)	**0.0392**	0.194	**0.0355**	0.186	**0.0439**	0.206
Onboard Computer (COMP, T_7)	**0.0549**	0.228	**0.0284**	0.167	**0.0877**	0.284
Processing/storage (PROC, T_8)	**0.0353**	0.185	**0.0142**	0.119	**0.0614**	0.241

Table 2. Technical Change for the Fleet:
Average Annual, all boats, 1985-1999

p.f. Standard

	1985-99		***1985-93***		***1994-99***	
	mean	*st. dev.*	**mean**	*st. dev.*	**mean**	*st. dev.*
$TECH_D$	**-0.0316**	*0.000*				
$TECH_T$	**0.0061**	*0.079*	**0.0027**	*0.062*	**0.0103**	*0.096*
$TECH_K$	**0.0046**	*0.014*	**0.0046**	*0.015*	**0.0045**	*0.012*
$TECH_E$	**0.0107**	*0.080*	**0.0073**	*0.064*	**0.0149**	*0.096*
$TECH_S$	**0.0077**	*0.164*	**0.0276**	*0.209*	**-0.0170**	*0.073*

p.f.
SPF

	1985-99		***1985-93***		***1994-99***	
	mean	*st. dev.*	**Mean**	*st. dev.*	**mean**	*st. dev.*
$TECH_D$	**-0.0281**	*0.000*				
$TECH_T$	**0.0146**	*0.073*	**0.0129**	*0.054*	**0.0168**	*0.085*
$TECH_K$	**-0.0074**	*0.017*	**-0.0092**	*0.019*	**-0.0052**	*0.015*
$TECH_E$	**0.0072**	*0.074*	**0.0037**	*0.067*	**0.0115**	*0.082*
$TECH_S$	**0.0067**	*0.138*	**0.0232**	*0.176*	**-0.0140**	*0.060*
EFFIC	**-0.0012**	*0.221*	**-0.0029**	*0.213*	**0.0008**	*0.231*

d.f. Standard

	1985-99		***1985-93***		***1994-99***	
	mean	*st. dev.*	**Mean**	*st. dev.*	**mean**	*st. dev.*
$TECH_D$	**-0.0325**	*0.000*				
$TECH_T$	**0.0117**	*0.055*	**0.0084**	*0.046*	**0.0158**	*0.065*
$TECH_K$	**-0.0002**	*0.0004*	**-0.0002**	*0.0005*	**-0.0001**	*0.0003*
$TECH_E$	**0.0114**	*0.056*	**0.0082**	*0.046*	**0.0156**	*0.065*
$TECH_S$	**0.0011**	*0.021*	**0.0036**	*0.027*	**-0.0019**	*0.010*

Table 3. Annual Technical Changes Estimates

by year, standard econometric p.f. model

	$TECH_T$	$TECH_K$	$TECH_E$
1985-86	0.0000	0.0000	0.0000
1986-87	0.0000	0.0112	0.0112
1987-88	0.0141	0.0011	0.0151
1988-89	-0.0056	0.0053	-0.0003
1989-90	-0.0226	0.0010	-0.0216
1990-91	0.0182	0.0011	0.0192
1991-92	0.0100	0.0042	0.0142
1992-93	0.0072	0.0127	0.0199
1993-94	-0.0353	0.0020	-0.0333
1994-95	0.0210	0.0000	0.0210
1995-96	-0.0270	0.0040	-0.0229
1996-97	0.0465	0.0040	0.0505
1997-98	0.0474	0.0090	0.0565
1998-99	0.0095	0.0080	0.0175

Table 4. Technical Change per Vessel:

standard econometric p.f. model

	1985-99		1985-93		1994-99	
	Mean	*st. dev.*	**Mean**	*st. dev.*	**mean**	*st. dev.*
Boat 1						
$TECH_T$	**0.0141**	*0.0512*	**0.0038**	*0.0107*	**0.0280**	*0.0791*
$TECH_K$	**0.0041**	*0.0153*	**0.0024**	*0.0160*	**0.0064**	*0.0156*
$TECH_E$	**0.0182**	*0.0523*	**0.0062**	*0.0187*	**0.0343**	*0.0780*
Boat 2						
$TECH_T$	**0.0307**	*0.1277*	**0.0223**	*0.0826*	**0.0419**	*0.1805*
$TECH_K$	**0.0068**	*0.0177*	**0.0071**	*0.0203*	**0.0064**	*0.0156*
$TECH_E$	**0.0375**	*0.1256*	**0.0294**	*0.0799*	**0.0482**	*0.1785*
Boat 3						
$TECH_T$	**0.0398**	*0.0831*	**0.0200**	*0.0437*	**0.0661**	*0.1176*
$TECH_K$	**0.0027**	*0.0102*	**0.0048**	*0.0135*	**0.0000**	*0.0000*
$TECH_E$	**0.0425**	*0.0866*	**0.0248**	*0.0567*	**0.0661**	*0.1176*
Boat 4						
$TECH_T$	**0.0059**	*0.0456*	**0.0000**	*0.0000*	**0.0137**	*0.0726*
$TECH_K$	**0.0082**	*0.0163*	**0.0095**	*0.0177*	**0.0064**	*0.0156*
$TECH_E$	**0.0140**	*0.0518*	**0.0095**	*0.0177*	**0.0200**	*0.0804*
Boat 5						
$TECH_T$	**0.0095**	*0.1398*	**-0.0303**	*0.1474*	**0.0626**	*0.1203*
$TECH_K$	**0.0054**	*0.0205*	**0.0047**	*0.0245*	**0.0064**	*0.0156*
$TECH_E$	**0.0150**	*0.1453*	**-0.0256**	*0.1588*	**0.0690**	*0.1159*
Boat 6						
$TECH_T$	**-0.0202**	*0.0619*	**0.0012**	*0.0033*	**-0.0486**	*0.0907*
$TECH_K$	**0.0068**	*0.0142*	**0.0071**	*0.0142*	**0.0064**	*0.0156*
$TECH_E$	**-0.0134**	*0.0658*	**0.0083**	*0.0139*	**-0.0423**	*0.0960*

Boat 7						
$TECH_T$	**-0.0030**	*0.0826*	**0.0241**	*0.0683*	**-0.0392**	*0.0920*
$TECH_K$	**0.0027**	*0.0182*	**0.0000**	*0.0205*	**0.0064**	*0.0156*
$TECH_E$	**-0.0003**	*0.0840*	**0.0241**	*0.0713*	**-0.0328**	*0.0948*
Boat 8						
$TECH_T$					**0.0178**	*0.0436*
$TECH_K$					**0.0000**	*0.0000*
$TECH_E$					**0.0178**	*0.0436*
Boat 9						
$TECH_T$	**-0.0157**	*0.0596*	**0.0000**	*0.0000*	**-0.0366**	*0.0913*
$TECH_K$	**0.0027**	*0.0102*	**0.0048**	*0.0135*	**0.0000**	*0.0000*
$TECH_E$	**-0.0129**	*0.0613*	**0.0048**	*0.0135*	**-0.0366**	*0.0913*
Boat 10						
$TECH_T$	**-0.0102**	*0.0383*	**-0.0179**	*0.0507*	**0.0000**	*0.0000*
$TECH_K$	**0.0027**	*0.0102*	**0.0048**	*0.0135*	**0.0000**	*0.0000*
$TECH_E$	**-0.0075**	*0.0404*	**-0.0132**	*0.0543*	**0.0000**	*0.0000*
Boat 12						
$TECH_T$	**-0.0045**	*0.0448*	**-0.0126**	*0.0358*	**0.0064**	*0.0563*
$TECH_K$	**0.0055**	*0.0139*	**0.0048**	*0.0135*	**0.0064**	*0.0156*
$TECH_E$	**0.0010**	*0.0407*	**-0.0079**	*0.0223*	**0.0128**	*0.0576*
Boat 13						
$TECH_T$	**0.0289**	*0.0851*	**0.0010**	*0.0387*	**0.0661**	*0.1176*
$TECH_K$	**0.0027**	*0.0102*	**0.0048**	*0.0135*	**0.0000**	*0.0000*
$TECH_E$	**0.0316**	*0.0847*	**0.0057**	*0.0408*	**0.0661**	*0.1176*
Boat 14						
$TECH_T$	**0.0056**	*0.0902*	**0.0098**	*0.1228*	**0.0000**	*0.0000*
$TECH_K$	**0.0068**	*0.0177*	**0.0024**	*0.0160*	**0.0127**	*0.0197*
$TECH_E$	**0.0124**	*0.0931*	**0.0122**	*0.1258*	**0.0127**	*0.0197*
Boat 15						
$TECH_T$	**-0.0074**	*0.0632*	**0.0000**	*0.0000*	**-0.0160**	*0.0971*
$TECH_K$	**0.0059**	*0.0143*	**0.0055**	*0.0144*	**0.0064**	*0.0156*
$TECH_E$	**-0.0015**	*0.0549*	**0.0055**	*0.0144*	**-0.0097**	*0.0826*

Boat 17						
$TECH_T$	**-0.0049**	*0.0183*	**0.0000**	*0.0000*	**-0.0114**	*0.0279*
$TECH_K$	**0.0027**	*0.0102*	**0.0048**	*0.0135*	**0.0000**	*0.0000*
$TECH_E$	**-0.0022**	*0.0216*	**0.0048**	*0.0135*	**-0.0114**	*0.0279*
Boat 18						
$TECH_T$	**0.0192**	*0.0813*	**-0.0126**	*0.0358*	**0.0617**	*0.1077*
$TECH_K$	**0.0068**	*0.0142*	**0.0095**	*0.0177*	**0.0032**	*0.0077*
$TECH_E$	**0.0260**	*0.0819*	**-0.0031**	*0.0276*	**0.0649**	*0.1149*
Boat 19						
$TECH_T$	**-0.0207**	*0.0715*	**0.0000**	*0.0000*	**-0.0482**	*0.1082*
$TECH_K$	**0.0027**	*0.0102*	**0.0000**	*0.0000*	**0.0064**	*0.0156*
$TECH_E$	**-0.0179**	*0.0722*	**0.0000**	*0.0000*	**-0.0419**	*0.1112*
Boat 23						
$TECH_T$	**0.0165**	*0.1056*	**0.0516**	*0.1055*	**-0.0303**	*0.0939*
$TECH_K$	**0.0041**	*0.0153*	**0.0024**	*0.0160*	**0.0064**	*0.0156*
$TECH_E$	**0.0206**	*0.1043*	**0.0540**	*0.1021*	**-0.0240**	*0.0975*
Boat 27						
$TECH_T$	**0.0229**	*0.0893*	**-0.0169**	*0.0413*	**0.0626**	*0.1097*
$TECH_K$	**0.0048**	*0.0166*	**0.0032**	*0.0188*	**0.0064**	*0.0156*
$TECH_E$	**0.0276**	*0.0895*	**-0.0137**	*0.0468*	**0.0690**	*0.1064*

Appendix Tables

Table A1. Coefficient Estimates for the Production Technology*

Table A1a. Production Function, Standard Econometric

Coeff	**Estimate**	*t-stat*	Coeff	**Estimate**	*t-stat*	Coeff	**Estimate**	*t-stat*
α_T	**-0.0316**	*-3.523*	γ_{K2}	**-34.7700**	*-2.021*	λ_{10}	**-0.1380**	*-0.594*
δ_{T1}	**-0.1247**	*-1.518*	$\gamma_{K2,S}$	**4.1142**	*2.387*	λ_{12}	**0.5656**	*3.674*
δ_{T2}	**-0.1012**	*-1.706*	γ_{K3}	**0.2977**	*1.057*	λ_{14}	**-0.3233**	*-0.967*
δ_{T3}	**0.1069**	*1.457*	γ_{K4}	**-0.0192**	*-0.293*	λ_{15}	**-0.3725**	*-1.181*
δ_{T4}	**7.0338**	*2.553*	γ_{K5}	**0.0382**	*0.854*	λ_{18}	**-0.7790**	*-2.723*
δ_{T4S}	**-0.6992**	*-2.522*	λ_1	**-0.0243**	*-0.073*	λ_{19}	**0.0253**	*0.080*
δ_{T5}	**-8.7439**	*-4.325*	λ_2	**0.0346**	*0.106*	α_1	**85.9446**	*2.338*
δ_{T5E}	**1.6374**	*4.262*	λ_3	**0.4177**	*3.064*	β_E	**0.6322**	*5.794*
δ_{T6}	**5.2228**	*2.583*	λ_4	**0.3100**	*1.040*	β_S	**-9.4984**	*-2.572*
δ_{T6E}	**-0.9702**	*-2.540*	λ_5	**0.4302**	*2.919*	β_O	**0.2218**	*2.141*
δ_{T7}	**-0.0209**	*-0.313*	λ_6	**-0.3125**	*-1.125*	β_{N1}	**-0.2774**	*-5.586*
δ_{T8}	**0.2898**	*4.389*	λ_7	**-0.3759**	*-3.067*	β_{N2}	**-5.7864**	*-3.893*
γ_{K1}	**6.5910**	*1.176*	λ_8	**0.1634**	*0.712*	β_{N2S}	**0.5900**	*3.950*
γ_{K1S}	**-0.7064**	*-1.270*	λ_9	**-0.0922**	*-0.972*			

Table A1b. Production Function, Stochastic Frontier

Coeff	**Estimate**	*t-stat*	Coeff	**Estimate**	*t-stat*	Coeff	**Estimate**	*t-stat*
α_T	**-0.0281**	*-5.176*	γ_{K2}	**-29.9139**	*-31.154*	λ_{10}	**-0.3683**	*-2.749*
δ_{T1}	**-0.1716**	*-3.386*	$\gamma_{K2,S}$	**3.6658**	*31.936*	λ_{12}	**0.8955**	*7.589*
δ_{T2}	**-0.0168**	*-0.439*	γ_{K3}	**0.2783**	*1.852*	λ_{14}	**-0.2122**	*-1.127*
δ_{T3}	**0.0801**	*1.456*	γ_{K4}	**-0.0425**	*-1.115*	λ_{15}	**-0.1975**	*-1.032*
δ_{T4}	**5.7514**	*5.251*	γ_{K5}	**-0.0397**	*-1.342*	λ_{18}	**-0.4502**	*-2.732*
δ_{T4S}	**-0.5562**	*-5.051*	λ_1	**-0.1487**	*-0.799*	λ_{19}	**0.2716**	*1.368*
δ_{T5}	**-8.1076**	*-8.618*	λ_2	**0.3781**	*1.963*	α_1	**88.1912**	*86.757*
δ_{T5E}	**1.5286**	*8.638*	λ_3	**0.6275**	*6.533*	β_E	**0.2398**	*3.946*
δ_{T6}	**2.6204**	*2.540*	λ_4	**0.4614**	*2.650*	β_S	**-9.4385**	*-70.792*
δ_{T6E}	**-0.4746**	*-2.428*	λ_5	**0.6748**	*4.805*	β_O	**0.3738**	*6.142*
δ_{T7}	**0.0312**	*0.545*	λ_6	**-0.1694**	*-1.043*	β_{N1}	**-0.2053**	*-8.118*
δ_{T8}	**0.1554**	*4.497*	λ_7	**-0.4321**	*-6.572*	β_{N2}	**-3.9263**	*-5.552*
γ_{K1}	**2.9230**	*3.812*	λ_8	**0.4859**	*2.877*	β_{N2S}	**0.4003**	*5.593*
γ_{K1S}	**-0.3834**	*-4.281*	λ_9	**-0.0409**	*-0.571*			

Table A1c. Distance Function (2 outputs), Standard Econometric

Coeff	**Estimate**	*t-stat*	Coeff	**Estimate**	*t-stat*	Coeff	**Estimate**	*t-stat*
α_T	**-0.0325**	*-4.546*	γ_{K3}	**-0.1950**	*-0.863*	λ_{12}	**0.2810**	*2.272*
δ_{T1}	**0.0409**	*0.624*	γ_{K4}	**-0.0012**	*-0.023*	λ_{14}	**0.0740**	*0.278*
δ_{T2}	**0.0053**	*0.112*	γ_{K5}	**-0.0009**	*-0.025*	λ_{15}	**0.1373**	*0.543*
δ_{T3}	**0.0176**	*0.301*	λ_1	**-0.2529**	*-0.952*	λ_{18}	**0.2349**	*1.000*
δ_{T4}	**0.2095**	*3.701*	λ_2	**0.3650**	*1.403*	λ_{19}	**0.4629**	*1.829*
δ_{T5}	**-0.1134**	*-2.294*	λ_3	**0.2838**	*2.625*	α_1	**26.1279**	*0.956*
δ_{T6}	**0.0805**	*1.429*	λ_4	**-0.0838**	*-0.353*	β_E	**1.2365**	*30.848*
δ_{T7}	**0.0533**	*1.014*	λ_5	**0.3182**	*2.758*	β_S	**-3.0945**	*-1.126*
δ_{T8}	**0.1448**	*2.863*	λ_6	**0.3191**	*1.435*	β_O	**0.0395**	*0.490*
γ_{K1}	**3.0144**	*0.723*	λ_7	**-0.0821**	*-0.831*	β_{N1}	**-0.0090**	*-0.212*
γ_{K1S}	**-0.4072**	*-0.986*	λ_8	**0.3649**	*1.997*	β_{N2}	**-0.0492**	*-1.016*
γ_{K2}	**-10.7709**	*-0.851*	λ_9	**0.0238**	*0.316*	η_{YR}	**-0.1981**	*-12.219*
$\gamma_{K2,S}$	**1.5374**	*1.213*	λ_{10}	**-0.2520**	*-1.361*	η_{YR2}	**0.0070**	*7.585*

*Parameters correspond to the following variables: t=time trend, T1=variable pitch propeller, T2=kort nozzle, T3=sonar, T4=netsonde, T4S=product of T4 and stock abundance, T5=global positioning system, T5E=product of T5 and fishing effort, T6=route tracer, T6E=product of T6 and fishing effort, T7=onboard computer, T8=amelioration of processing and storage, K1=gross tonnage, K1S=product of K1 and stock abundance, K2=length, K2S=product of K2 and stock abundance, K3=hull type, K4=number of drums, K5=number of engine changes, λ_1 - λ_{19} = dummy variables for each vessel, E=fishing effort, S=stock abundance ($LPUE_{-1}$), O=owner, N1=number of net otter trawls, N2=number of mid-water trawls, N2S=the product of N2 and $LPUE_{-1}$, YR=Bluefish/Whitefish, and YR2=YR^2. All variables, except time and change counters, are in natural logarithms.

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