Productivity Growth, Catchability, Stock Assessments, and Optimum Renewable Resource Use

by

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Abstract

Productivity growth substantially impacts rent-maximizing resource stocks, and can lead to economically overfished stocks, where BMEY < BMSY, illustrated by an empirical example. Bioeconomic models can give biased results and policy advice when not accounting for time-varying catchability -- notably productivity growth -- and density-dependent catchability, and not distinguishing between fishery-dependent and fishery-independent data and implications for catchability, modeling, and applicability of results. Productivity growth, as a component of time-varying catchability, also impacts stock assessments. CPUE standardization and productivity measurement both face an identification issue in disentangling changes in resource stocks and productivity as well as endogenous regressors for which there are potential identification strategies.

Key words: productivity, catchability, bioeconomics, stock assessments, maximum economc yield

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Productivity growth impacts the optimum dynamic exploitation of renewable resources such as fisheries. Nonetheless, the normative bioeconomics literature has largely overlooked the growing body of economic literature on the positive economics of productivity growth in capture marine fisheries, reviewed by XXX in this volume.[[1]](#footnote-1)

Productivity growth can potentially lead to substantially different dynamic economic optimal paths, resource stock levels, and policy implications than that concluded by the bulk of the bioeconomics literature. This literature and the economic policies that follow are entirely static in productivity growth. This literature recommends dynamic maximum economic yield (MEY) and biomass (or numbers of animals) of the resource stock (BMEY) corresponding to optimum dynamic scale efficiency, excludes technical and allocative efficiency, and imposes a spurious no-growth, steady-state equilibrium (Squires and Vestergaard 2013).[[2]](#footnote-2) This literature further recommends BMEY greater than the maximum sustainable yield resource stock (BMSY), because a larger resource stock lowers exploitation (density-dependent search and harvest) costs that raise economic rent (Grafton et al. 2007, World Bank and FAO 2009, OECD 2010).

The bioeconomics literature reaches additional conclusions that may not hold when incorporating productivity growth. The perceived crisis in global fisheries (World Bank and FAO 2009, Global Oceans Commission 2014) is likely misstated in terms of economic rent, effective effort, and natural capital when productivity growth is accounted for in normative dynamic analysis (Squires and Vestergaard 2013). Recommended optimum fleet sizes, effort or physical capital levels, resource stock targets, and policy instruments simply do not match the more productive technology and its continual growth that are ongoing but are unaccounted for in current dynamic models. Rebuilding strategies (OECD 2010) do not correspond to BMEY when accounting for productivity growth. Productivity growth can lead to risk of optimal extinction, and more generally biodiversity loss, greater than considered by Clark (2010) and others. The bionomic (open-access) equilibrium of Gordon (1954) may only exist, if at all, at levels much lower than currently held.

Productivity measurement is also closely related to issues that arise with catchability in population assessments and that also bear upon bioeconomic models.[[3]](#footnote-3) The population assessment, bioeconomic, and productivity literatures grapple with, or should grapple with, catchability that is potentially time-varying and density-dependent and with the implications from using fishery-dependent and fishery-independent data.[[4]](#footnote-4)

This paper extends the bioeconomics literature to incorporate productivity growth. We also discuss the relationship between productivity growth and time-varying and density-dependent catchability and fishery-dependent and –independent data used in population assessments and that bioeconomic models should consider. We illustrate the impact of productivity growth, using a Malmqvist-Törnqvist index, upon MEY and BMEY for the US and Canada Pacific coast albacore (*Thunnus alalunga*) troll fishery. We employ a bioeconomic model that accounts for both disembodied and embodied technical change (see Solow (1960) and Hulten (1992)). We eschew a spatial bioeconomic model with density-dependent fish movement between spatially linked distinct populations or substocks, because supporting empirical biological evidence is absent for many fish species, and especially for albacore, which make ontogenetic migrations (Squires et al. in press).[[5]](#footnote-5)

Section 2 discusses the relationships between productivity measurement and catchability, population assessments, bioeconomic models, and the use of fishery-dependent and -independent data. Section 3 summarizes growth accounting and productivity, the Malmquist productivity measure, and bioeconomic models. Section 4 incorporates productivity growth into the Golden Rule of renewable resource economics. Section 5 provides empirical results and discusses policy implications. Section 6 concludes.

**2. Catchability and fishery-dependent and –independent data**

This section first raises issues in catchability and the implications for productivity measurement and bioeconomic models. The section next discusses density-dependent catchability. The section then discusses time-varying catchability and the implications for stock assessments from the economic theory of productivity measurement, economic index numbers, and technological change. The section then discusses the implications of fishery-dependent and fishery-independent data for measuring productivity growth. The section concludes with implications of productivity theory for stock assessments.

**2.1. Issues in catchability**

Several questions arise for productivity growth measures and bioeconomic models and their relationship to catchability and population assessments and the use of fishery-dependent and –independent data.[[6]](#footnote-6) Catchability, of which productivity is a part, may be density-dependent (elaborated upon below), so that bioeconomic models and population assessments may not represent the entire population (Hannesson 1983, Wilberg et al. 2010). Second, both productivity measures and stock assessments may use all or part of the same fishery-dependent data, potentially requiring a strategy to disentangle changes in resources stocks from changes in productivity. One such strategy may be to use fishery independent data and another identification strategy uses the structure of fishery-dependent data as an identification strategy in VPA models (Ekerhovd and Gordon 2013). Third, productivity measures may use estimates of stock size from assessments that incorporate time-varying catchability. This can confound the productivity measures, since it is only one of several potential sources of time-varying catchability; again, an identification strategy is required. Fourth, productivity measures can employ absolute resource stock measures or relative changes in stocks, where the latter are generally considered more reliable and the former are not always available (e.g. from yield-per-recruit analysis, Maunder and Punt 2013). Finally, catchability may be effort-dependent, in which catchability varies with the level or scale of effort and the crowding externality (Hannesson 1983). However, other than noting knowledge spillovers that depend upon the level of investment, we leave this topic for future discussion.

Before proceeding, we note that CPUE, a widely used measure of relative stock abundance and/or of local density, is an average product of effort. In contrast, productivity is measured as total factor productivity (TFP). In particular, TFP is measured as a residual after accounting for changes in all inputs, including resource stocks (Squires 1992), and uses many of the same fishery-dependent data as CPUE estimates and most stock assessments.[[7]](#footnote-7)

**2.2. Density-dependent catchability**

Productivity measures, bioeconomic models, and stock assessments are all potentially subject to density-dependent catchability of harvesting vessels. A stock is not evenly distributed and changes spatially and temporally as its abundance changes (Hannesson 1983, Hilborn and Walters 1992, Quinn and Deriso 1999, Wilberg et al. 2010). In addition, fisher search is nonrandom or there can be gear saturation or density-dependent gear avoidance behavior, all of which can affect catchability in fisheries and surveys. Fleet spatial expansion can also affect density-dependent catchability.

Density-dependent catchability has implications for use of fishery-dependent and fishery-independent data. Stock assessment from a restricted part of a stock’s range requires the stock to decrease in the same proportion across the entire range in which it is fished (Hilborn and Walters 1992, Quinn and Deriso 1999, Wilberg et al. 2010). For catchability to represent abundance, averaging catch rates for any time period over only areas fished requires assumptions about what catch rates would have been in areas that had not yet or were no longer fished (Walters 2003, Maunder et al. 2006). Ignoring unfished areas and averaging only over areas fished (i.e. using fishery-dependent data) essentially assumes fleets behaved the same in both fished and unfished areas, and leads catchability and productivity measures to potentially exhibit “hyperstability” or “hyperdepletion”. Density-dependent catchability typically increases as abundance declines, thereby causing “hyperstable” CPUE, in which CPUE remains high despite decreases in abundance (Hannesson 1983, Hilborn and Walters 1992, Quinn and Deriso 1999).

Density-dependent catchability is not only a concern for stock assessments it is also an issue for bioeconomic models, especially when calculated using fishery-dependent data. This is because bioeconomic models are typically meant to apply to the entire fishery, whether fished or unfished, which means that they can suffer from the same uncertainties as that of stock assessments. Density-dependent catchability using fishery dependent data is less troublesome to measures of productivity growth or technological change, because these are positive measures based on “what is”, i.e. actual fleet behavior and performance. When these productivity measures are used in bioeconomic models, the issue of density-dependent catchability does not arise unless the productivity measure pertains to only some of the relevant vessels or fleet expansion to unfished areas is anticipated. Of course, there may remain other sources of density-dependent catchability.

**2.3. Time-varying catchability**

In contrast to the bioeconomics literature, the population dynamics literature accounts for time-varying catchability (Wilberg et al. 2010).[[8]](#footnote-8) [[9]](#footnote-9) Not accounting for time-varying catchability would otherwise lead to biased estimates of stock size and stock productivity. Anthropogenic, environmental, biological, and management processes may drive changes in catchability over time. Time-varying catchability can be found in both fishery-dependent and –independent data sources, although it is generally believed more prevalent in fishery-dependent data.

Several approaches standardize effort or CPUE data series for time-varying catchability or allow catchability to vary over time (Maunder and Punt 2004, Maunder et al. 2006, Wilberg et al. 2010). Standardization aims to ensure that the catchability coefficient can be assumed constant, i.e. control effects other than those caused by changes in stock size, such as changes in economic efficiency or technology, density or effort dependence, species targeting, environment, and dynamics of the fleet or population (especially factors leading to density-dependent catchability). Effort or CPUE is adjusted for known changes in efficiency, or effort in other gears is converted to a standard gear in which catchability is not thought to have changed. The various methods for standardization of catch and effort data define the efficiency of a fishing vessel as its ‘fishing power’ relative to that of a standard (and perhaps hypothetical) fishing vessel, most commonly by the ratio of the two CPUEs (Maunder and Punt 2004).[[10]](#footnote-10)

Economic theory provides a number of insights for standardization. Standardization employing a standard production unit can be viewed in economics as a multilateral productivity index or a frontier function estimated using panel data or deterministic or stochastic half-sided error terms. This a-theoretical approach assumes a single aggregate technology across multiple fleets/gears, which allows aggregating through fixed proportions. This also implies Hick’s neutral technical change with a static-reference technology base including fleet and time period (see the DEA Malmqvist literature for implications). Furthermore, constant and/or time-invariant returns to scale is typically assumed, which, allows no differences over time in the structure of production and does not satisfy all the desirable properties of economic index numbers. Specifically, assuming a particular functional form for the aggregator index of catch and effort is prone to potentially restrictive properties, and may be subject to intransitive bilateral comparisons and failure of Fisher’s factor reversal test (an issue for bioeconomic models). Finally, CPUE standardization can only correct for measured factors that affect catchability and requires available data for each factor (Wilberg et al. 2013). Ignoring or down-weighting a catchability index that may have changed also accounts for time-varying catchability (Wilberg et al. 2010).

As an alternative to standardization to account for time-varying catchability, catchability can be explicitly modeled as a function of time (Prager 1994, Wilberg et al. 2010), including explicitly technical progress (Hannesson 1983). This approach captures all sources of time-varying productivity, so that changes in productivity are conflated with abundance (and perhaps environment), and confronts the same problem as TFP measurement, that of disentangling TFP and stock changes with a time trend (or related variable). Simply put, stock assessments aim to remove the effect of productivity growth from stock estimates and economists want to remove the effect of stock changes from productivity growth; both require an identification strategy to disentangle the two sources of change, often using the same fishery-dependent data.

Economic theory has implications for catchability modeled as a function of time. Such an approach typically only captures Hick’s neutral disembodied technical change. Interactions between time and explanatory variables allow for biased technical change, but complicate use of time to measure abundance changes (see Maunder and Punt 2004). This approach does not typically capture embodied technical change,[[11]](#footnote-11) or time-varying changes in technical efficiency, or nonlinear relationships between effort and technical change such as congestion spillovers (Hannesson 1983) and knowledge spillovers. A linear time trend captures only a constant rate of technological change and a quadratic allows a variable rate. Time specified in blocks or steps is related to the general index of technical change (Baltagi and Griffin 1988). Catchability can also be modeled as a function of density or an environmental variable, although this approach excludes productivity growth, essentially assuming it is static over time. Finally, catchability can be allowed to change over time using state space models. Random walks have been used, and perform better with slower changing populations. All these standardization approaches are a-theoretical vis-à-vis the economic theory of technological change and more generally, productivity growth and properties of economic index numbers and make a number of implicit assumptions that can affect results.

**2.4. Productivity measurement using fishery-dependent and –independent data**

TFP measures calculated using fishery-dependent data may be confounded when using stock abundance measures from stock assessments also using fishery-dependent data. Stock assessments accounting for time-varying catchability already account for growth in TFP (and other time-varying factors). The TFP residual then measures, at least in part, what has already been accounted for and using the same data. The TFP residual may or may then not be biased and account for all time variation, depending upon a number of factors that identify the difference between variations in TFP and the stock. Such factors include whether the TFP estimate is for a fleet accounting for only a portion of the stock’s total fishing mortality (the stock assessment used data from additional fleets or areas that the TFP measure does not), whether the TFP measure uses additional data that the stock estimate does not (such as investment in technology-embodied physical capital, e.g. adoption of echo sounders), how the stock assessment accounts for time varying catchability (especially functions of time) if at all, whether the stock estimates employ other sources of data, notably fishery-independent[[12]](#footnote-12), and the type of assumptions made in the assessment.[[13]](#footnote-13) Yet another alternative using integrated stock assessment models measures TFP growth using stocks estimated employing fishery independent data, employ the productivity growth measure in additional stock estimates, and reestimates productivity growth using all data, etc., in an iterative approach.[[14]](#footnote-14)

Stock estimates from fishery independent data may not confound TFP measures, since stock estimates are exogenous to the fleet and identified. Surveys providing fishery independent data that use a standardized design and cover the full potential range of the stock will also be least susceptible to time-varying catchability (Wilburg et al. 2010). However, stock assessments using both fishery dependent and independent data tend to outperform those using only fishery independent data. Stocks estimates using only fishery-independent data my not reflect the abundance and availability actually encountered by vessels and thereby give less precise productivity measures.

**2.5. Incorporating productivity growth into stock assessments**

There is not an explicit, theoretically consistent mechanism to incorporate productivity growth into population assessments, and this paper provides some insights. Notably, when the effort measure excludes the physical capital stock in general and investment in this stock in particular (e.g. echo sounders), time-varying catchability does not have a mechanism to incorporate technology that enters through investment in physical capital (i.e. embodied technical change), although if the time trend captures the productivity residual, it does (Hulten 1992). Depending upon how effort is measured, allocative efficiency may not be considered. Similarly, without a production frontier, technical efficiency is excluded. Knowledge and congestion spillovers that create a nonlinear catch-effort relationship are excluded. In principle, the catchability coefficient can be decomposed into one part systematically accounting for productivity growth theoretically consistent with microeconomic and economic growth theories and calculated using fishery-dependent data and a residual catchability part accounting for other sources of time variability, such as environmental changes. Many of these other components cannot be estimated without auxiliary information, and changes in selectivity (age- or length-based patterns in catchability) may also be conflated with changes in overall catchability (Willberg et al. 2010). When abundance indices are calculated with fishery-independent data, the possibility arises for constant catchability.

Bioeconomic models estimated simply with time-varying catchability using standard stock assessment approaches only account for disembodied technical change, and exclude: investment in physical capital that incorporates embodied technology; changes in technical efficiency; input substitution; and knowledge and congestion spillovers, all economically endogenous sources of change. Bioeconomic models estimated with time-varying catchability and fishery-dependent data face potential density-dependent catchability issues, and if estimated with fishery independent data may not accurately account for changes in technology or technical efficiency. Bioeconomic models estimated with fishing time (e.g. days/sets) as a measure of effort assume time rather than physical capital as the limiting input and preclude investment in physical capital, embodied technical change, input substitution, and congestion and knowledge spillovers as economically endogenous sources of change. Bioeconomic models estimated with standardized effort data also face potential economics issues related to standardized effort discussed above.

**3. Growth accounting and Malmqvist-Törnqvist productivity measures**

We first develop the productivity growth residual through growth accounting that we subsequently estimate. Let denote catch in time *t*, denote variable inputs, denote physical capital stock, , denote natural resource stock, dots denote proportional rates of growth, is cost share of physical capital, denote rate of embodied technical change, and denote constant rate of Hick’s neutral, exogenous, disembodied technical change. Under constant returns to scale in effort, Hicks neutral exogenous technical change, full capacity utilization for , full technical efficiency for reasons other than embodiment of technology in capital, input allocative efficiency in the aggregator functions for and , and no changes in output quality) (Hulten 1992, Squires 1992): . Rearranging gives the growth rate in the Solow TFP residual: . is then equal to . may not be uniformally distributed, such as with schooling fish. can then be weighted, giving (Hannesson 1983). For both the sole owner and non-uniformally distributed , there is no longer a one-to-one relationship between and .

The Malmqvist TFP index between periods t and t-1 can be approximated by the ratio of a Törnqvist output index to a Törnqvist input index under constant returns to scale in both periods (Caves et al. 1982). This provides a “Hicks-Moorsteen” TFP measure. To employ economic index numbers, we assume competitive input and output markets, a plausible assumption here.

The Törnqvist effort index is:

, (1)

where , , and is the price of , i = 1,2. It is equivalently:

. (2)

The Malmqvist-Törnqvist bilateral TFP index with a single output is:

(3)

,

or equivalently is:

. (4)

A single input is used with a fixed proportions technology. This index imposes both technical and allocative efficiency and constant returns to scale. Technical efficiency implies evaluating temporal changes in production frontier without deviations due to “catching up” or “falling behind”.

The TFP index for our albacore fishery case study is comprised of US vessels over 1981-1989 and both U.S. and Canadian vessels over 1990-2009. We employ the geometric mean of the Törnqvist TFP indices for the U.S. and Canada to obtain an aggregate Malmqvist- Törnqvist TFP index for the years 1990-2009:

. (5)

The albacore stock is assessed without time-varying catchability using an integrated analysis (Stock Synthesis 3) using both fishery-dependent and independent data (WCPFC 2014). Statistical (Hausman) tests indicated that the stock estimate is exogenous to effort, and this identification should hold for the deterministic productivity indices (Squires and Vestergaard 2013). We use the S4 (base case) and S2 (third case) time-invariant catchability coefficients from the 2014 assessment (WCPFC 2014).

**4. Productivity growth and the Golden Rule of renewable resource economics**

The Golden Rule with disembodied and embodied technical change, full capital utilization, and accounting for technical inefficiency in the yield frontier (and allocative efficiency with effort) is:[[15]](#footnote-15)

. (6)

where the biological (logistic) growth function is , P denotes constant ex-vessel price, denotes the discount rate, denotes a nonpositive, half-sided error term capturing time-varying deviations from the best-practice frontier or technical inefficiency and allows for “catching up” and “falling” behind the frontier over time, denotes constant social discount rate, is the time- and density-invariant catchability coefficient (as used in the international stock assessment), and is constant cost per unit of effort.

Disembodied Hicks neutral technical change, here measured by constant , could be expanded to included a quadratic term, , so that it is time-varying; ideally, Step changes (Baltagi and Griffin 1988) and stochastic shocks (Fissel and Gilbert 2010) are also possible.  
 The first term from the left in (6) is instantaneous marginal productivity of , second term is modified marginal stock effect (impact of upon costs), and third term is the new marginal technology effect (impact of changes in technical efficiency, given allocative efficiency with effort, and disembodied and embodied technical change upon costs). Assuming constant and with Cobb-Douglas functional form implies , where is average measure of the level of best-practice technology in time t that depends on the underlying efficiency parameters and age structure of the entire capital stock averaged over all vintages. When measuring productivity growth as a residual, becomes , where denotes the instantaneous rate of productivity growth as discussed above and which we approximate in discrete time as .  
 Overall time-varying catchability becomes the product of catchability that is time-invariant vis-à-vis productivity growth, but could be time varying for other reasons (e.g. envirionment), and could be density-dependent (neither of which are explicitly specified in ), and a time-varying catchability term estimated from fishery-dependent data as in economic productivity analyses. Identification issues arising when disentangling temporal changes in productivity and when using fishery-dependent data apply here.

We explore four empirical cases. The base case specifies a constant catchability coefficient and the stock exponent equal to one. The second case specifies the stock exponent equal to 0.9[[16]](#footnote-16). The third case specifies the catchability coefficient higher than the base case. The fourth case specifies a lower rate of productivity growth. Together these cases will illustrate the impact of the catchability coefficient.  
 There is not a classic no-growth, steady-state solution to , but instead a balanced growth path eventually limited by ’s productivity. The marginal stock effect declines over time, and density-dependent harvest costs can be more than balanced by technological change that lowers harvest costs. Over time, both the marginal stock and marginal technology effects decline, requiring continuing increases in own rate of return to the resource stock, , given constant . Higher rates of or productivity growth hasten the decline of .  
 The limit rent-maximizing resource stock as time approaches infinity is (Squires and Vestergaard 2013):

. (10)

where denotes the intrinsic growth rate. Because the sum of terms in brackets is less than or equal to 2, , which contrasts with dynamic economic optimum under static technology generally exceeding (Grafton et al. 2007). Essentially, over an infinite time horizon, technological progress erodes costs close to 0, and is determined solely by . , so declines with technical progress, and , so that the declining stock levels out for a given rate of continuous productivity growth for the balanced growth path over an infinite time horizon, and the scale, technically efficient, and allocative efficient stock declines at a slower rate toward a stock level for which . When , , i.e. extinction is optimal under continuous productivity growth. In the intermediate and realistic case, and , which contrasts with the static-in-technology dynamic model in which for most reasonable level of costs and prices and in which density-dependent costs are more important.

The open-access resource stock is:

, (11)

where again the productivity growth rate replaces .

**5. Empirical results and policy implications**

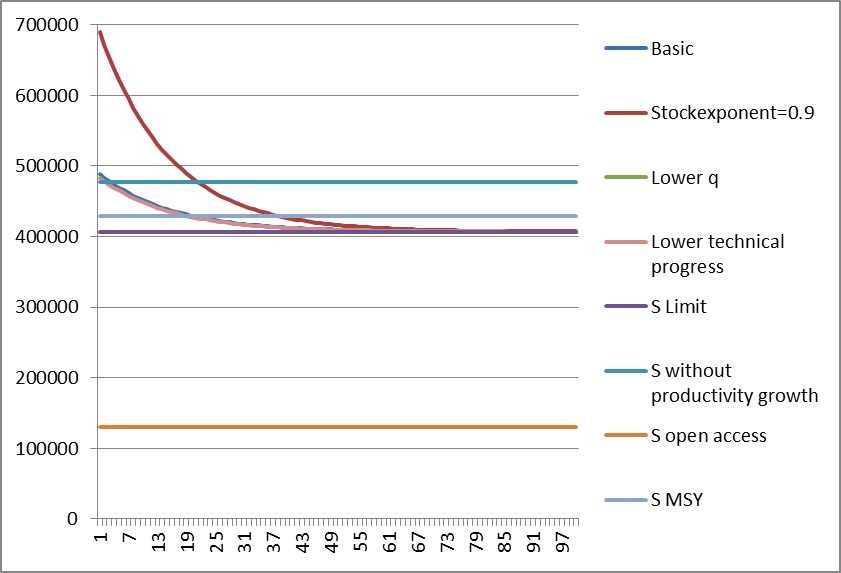
We examine the single-species U.S. and Canadian troll fleets fishing for North Pacific albacore (*Thunnus alalunga*). These fleets form part of the North Pacific albacore fishery of troll, pole-and-line, and other surface gear for Taiwan, Japan, Korea, U.S., and Mexico. Albacore migrate from off Japan across the Pacific at around 40ºN to the U.S. Pacific coast along the ocean surface, then some swim north and others south. They swim in schools at speeds up to 80 km per hour and are found near dynamically evolving ocean fronts and temperature breaks. The unregulated industry and absence of bycatch imply no regulatory-induced or related directed technical change.

Trolling for albacore entails towing 10-20 lines each rigged with a jig shaped to look like squid on the ocean surface, behind a slow-moving boat. Pole-and-line gear consists of poles rigged with a feathered jig mounted on a barbless hook. For this method to be effective albacore are attracted to the ocean surface alongside the vessel by chumming with live bait and by the vessel itself. Vessels find the albacore using physical capital embodied with information technology, including sensing devices to find temperature breaks, satellite data to identify ocean fronts , GPS and echo-sounders. There is minimal catch of other species, so that only a single-product is produced. .

Vessels are relatively small and family owned, with U.S. vessel length averaging about 13 meters, and harvest albacore from about 160°W to the North American Pacific coast and from 30°N to 55°N. Other than gear and fishing finding equipment the major on-vessel innovation) is an on-board freezer system.

The empirical analysis employs the catch and days fished data used in international stock assessments (WCPFC 2010). From the albacore stock assessment, [[17]](#footnote-17) *K* = 857,138 mt and *MSY* = 105,571 mt. We calculate International stock assessments also provide exogenous estimates of resource stock biomass for fish age one plus (WCPFC 2014). c (US$2001) is set at the 1981-2009 mean, giving $1164.72/vessel-day, where costs include operating costs of fuel, oil, food, gear, and labor. P, a weighted average of brine frozen, blast bled, and iced/fresh, is $3,515.34/mt. The catchability coefficients were in the base case 2.55E-0.6 and in the third case 2.13E-03 (see Table 5.3. in WCPFC 2014).

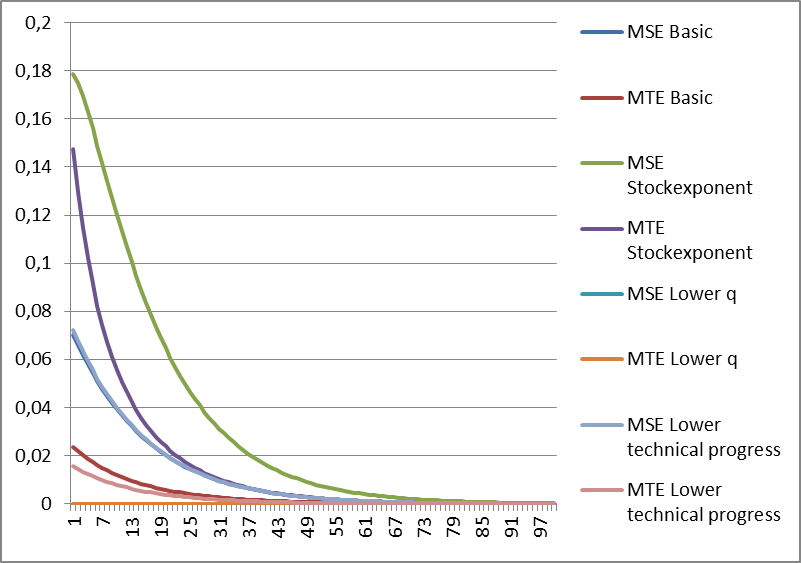
The arithemetic average annual TFP growth with equal weights for US and Canada is 7.12%, which is used as the base case. The cost-share weighted annual TFP growth is 4.67 percent, with annual cost shares that change each year and average 91.12 percent for the US, is used in case four to illustrate the impact of lower technical progress.



*Figure 1. Stock paths*

Figure 1 illustrates northern albacore stocks over 100 years assuming logistic growth and overall U.S. and Canada fleet productivity growth and only source of time-varying catchability. Eight stocks are depicted, in the four cases, , optimum stock without productivity growth and open access stock for the base case and .

The results demonstrate first of all that , and that BMEY with productivity growth ( that excludes the marginal technology effect (i.e. no productivity growth) is a misleading and false optimum. Resource stocks and biodiversity in general face greater pressures than realized, and there is an opportunity cost in foregone rent to imposing static productivity growth and a spurious no-growth steady-state equilibrium. Second, the optimal approach paths to (the limit stock) are different in the four cases. In the base case, the stock begins above BMEY with productivity growth and declines over time to the limit stock. With a stock exponent equal to 0.9, the stock begins much higher, indicating higher marginal stock and technological effects. With a lower catchability coefficient, the marginal stock and technological effects vanish, and the stock begins very close to the limit stock. In the case with lower technical progress, the optimal stock path follows closely the base case.



*Figure 2. Marginal stock effects and marginal technology effects.*

Figure 2 illustrates marginal technology and marginal stock effects over 100 years, showing their relative importance and decline of the marginal stock and technology effects over time. In all cases, the marginal stock effects are higher than the marginal technological effects because the productivity growth is lower than the average stock biomass growth. Compared to the base case, both the marginal stock and the marginal technological effects increase with a stock exponent = 0.9 and the differences between the effects narrow. Both effects vanish, as noted, with a lower catchability coefficient, which show no cost or technological gains of higher stock levels. With lower technical progress, the marginal stock and marginal technological effects are lower than, but similar to, the base case.

**6. Concluding remarks**

This paper discussed four topics related to productivity growth: its impact upon BMEY and bioeconomic modeling; it relationship to time-varying catchability; its relationship to fishery-dependent and –independent data and density-dependence in bioeconomic models; and identification in disentangling changes in resource stocks and productivity as well as endogenous regressors.

Productivity growth substantially impacts rent-maximizing level resource stocks, and can lead to BMEY < BMSY, i.e. overfished stocks, counter to conventional wisdom. The distance between BMEY and BMSY is determined by the intrinsic growth rate and interest rate. The marginal stock effect has no impact upon the final result, and only affects the approach path to BMEY, which is determined by all the biological and economic parameters. Productivity growth, as a component of time-varying catchability, also impacts stock assessments.

CPUE standardization and productivity measurement both face an identification issue in disentangling changes in resource stocks and productivity as well as endogenous regressors and issues of aggregation. This paper continues discussion of potential identification strategies.

Our results show that bioeconomic models can give biased results and policy advice when not accounting for time-varying catchability -- notably productivity growth -- and density-dependent catchability. Biased bioeconomic results and policy advice also arise when not distinguishing between fishery-dependent and fishery-independent data and the implications for catchability, modeling, and applicability of results.

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1. See recent bioeconomics reviews by Conrad and Smith (2012), Squires and Vestergaard 2013, and Kronbak et al. (2013), plus Clark (2010). [↑](#footnote-ref-1)
2. Scale efficiency is the optimum level of effort, technical efficiency is maximum catch for a level of effort and resource stock in a time period, and allocative efficiency is the cost-minimizing input combination comprising effort or the revenue-maximizing output combination in a time period. [↑](#footnote-ref-2)
3. Catchability has several definitions (Wilberg et al. 2010). One is the parameter that relates an index of relative abundance to population size (absolute abundance). Another is the proportionality parameter between fishing effort and fishing mortality or the portion of the stock captured by one unit of effort. The earliest theoretically rigorous economics paper on time-varying and density-dependent catchability of which we are aware is Hannesson (1983). Ekerhovd and Gordon (2013) also raise the identification issue when using resource stock to evaluate catch-effort (or by extension productivity) relationships, and propose a specific identification strategy for VPA models. Our paper builds off both papers. [↑](#footnote-ref-3)
4. The most common source of fishery-dependent data is catch and effort information from commercial or recreational fishers. Surveys and life history studies provide some of the most important sources of fishery-independent data. Population assessments have long recognized these issues as we discuss below. [↑](#footnote-ref-4)
5. Source-sink larval or fish movements between patches or meta-populations also do not realistically depict spatial processes with albacore (and most other small and large pelagic species). Albacore broadcast spawn, and (recruited) albacore tend to concentrate along temperature breaks and dynamic oceanic fronts. Expansions and contractions of species and corresponding long-term spatial movement centered around core habitat area with environmental change (the “basin model”, MacCall 1990) may also not apply. [↑](#footnote-ref-5)
6. Our discussion follows the bulk of the population dynamics literature and is couched in terms of surplus production models. In surplus production models, catchability may be represented by a single coefficient. However, Eric Thunberg notes that in age-based or cohort models catchability is represented as a vector. If selectivity is dome shaped, density-dependent growth may influence the number of ages that remain susceptible to the gear. [↑](#footnote-ref-6)
7. Excluding the resource stock leaves a TFP residual that reflects changes in both productivity and the resource stock (Squires 1992). CPUE as a measure of abundance faces considerable problems (Maunder et al. 2006). Further, CPUE used as a measure of abundance in productivity studies creates an identification issue, since catch and effort are on both sides of the equation, leading to biased and inconsistent estimates. [↑](#footnote-ref-7)
8. The population dynamics literature does not explicitly account for productivity growth, which is one component of time-varying catchability. The “fishing power” literature is not based upon a consistent and comprehensive theory of production and is largely a reduced form statistical analysis. [↑](#footnote-ref-8)
9. An alternative, not discussed here, is time-varying selectivity. [↑](#footnote-ref-9)
10. Parameter estimates are likely biased and inconsistent due to endogenous explanatory variables (unless found otherwise through Hausman tests), such as effort (days/sets/trips) or catch of other species, requiring an identification strategy and instrumental variable estimation. Standardization often overlooks heteroscedasticity and sometimes serial correlation and cluster-specific heteroscedasticity and serial correlation with panel data. [↑](#footnote-ref-10)
11. Unless indicators such as new use of a technology (e.g.GPS) are included as regressors, but then run into the problem of varying rates of adoption and diffusion throughout the fleet plus knowledge spillovers. [↑](#footnote-ref-11)
12. Stock assessments employing both fishery independent and dependent data, notably integrated assessments, utilize considerable information exogenous to the productivity measure, including cohort, gender, age-length or size-length, and recruitment (see Maunder and Punt 2013). [↑](#footnote-ref-12)
13. Identification of inputs (effort) in econometric estimates of productivity growth and subsequent instrumental variable estimation if necessary are likely not issues with contemporary stock assessment approaches, such as integrated approaches or perhaps even VPA supplemented with additional information, which utilize considerable information exogenous to the productivity measure, including cohort, gender, age/size-length, recruitment, etc. Moreover, both fishery-independent measures of abundance (when available) and fishery-dependent data on catch and effort impose considerable structure such as growth and recruitment functions that address the identification problem. [↑](#footnote-ref-13)
14. Mark Maunder suggested this possibility. This “two-step” approach differs from integrated analysis in which the parameters of the population dynamics model and those related to catch-effort standardization are estimated simultaneously by optimizing an objective function for all sources of data available to the stock assessment model (Maunder and Punt 2004). [↑](#footnote-ref-14)
15. See Fissel and Gilbert (2010) for non-constant rates of technical change and productivity growth. [↑](#footnote-ref-15)
16. This can be interpreted as the catchability coefficient is a function of stock. [↑](#footnote-ref-16)
17. A comprehensive bioeconomic model for policy rather than illustration entails including productivity estimates of all fleets harvesting albacore and would also specify age-structured population dynamics rather than the Schaefer surplus production model. [↑](#footnote-ref-17)