Evaluating the Impact of Sector Management on the Productivity of New England Groundfish Fisheries

Abstract

In this paper, we compute individual revenue-based and catch-based Technical Efficiency across time using stochastic production frontier method for the New England Groundfish Fisheries. We develop tests to empirically distinguish three channels of impact of sector management on the productivity of the fisheries, and we find that stock effect is more important than price effect and sector effect. Stock effect increases the group mean of catch-based Technical Efficiency by 8.68%. We also find that vessels make entry and exit decisions according to the revenue-based Technical Efficiency and vessels make sector participation decisions according to both revenue-based and catch-based Technical Efficiency. Generally speaking, vessels with lower value-based TE tend to exit the fishery and vessels with higher Technical Efficiency tend to join sectors.

1. Introduction

On May 1st, 2010, New England groundfish fishery started a new management regime, under which fishermen can voluntarily form sectors, with each sector constrained by a subdivision of Annual Catch Limits (ACLs). In essence, this new regime is a quota approach, though having a unique feature of voluntary sectors. Like many other fishery policies, two crucial factors need to be considered to understand this new regime: whether it can prevent fish stocks from declining, and whether it can improve the economic performance of the fishery. Since productivity change is a very important indicator of performance (Jin et al. 2002), this paper focuses on analyzing the impact of this new management regime on fish stock and productivity in the New England Groundfish fishery, and provides interpretations for the change. As the details of program design and implementation vary considerably (Townsend et al. 2008) and matter a lot to the policy impacts including impacts on stock and productivity, it is important to carefully understand the underlying mechanism and distinguish the impacts by different components, i.e. quota and sector management.

The New England Groundfish Fishery is a typical multispecies complex consisting of altogether 13 fish species[1]. Before the sector management, the New England groundfish fishery is regulated under a limited access program with restrictions of individual vessels' days at sea (DAS), area closures and trip limits. Under the new regime, 9 of 13 groundfish

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[1] See Holland (2007) for a history of the development of sectors in the NE groundfish fishery.

species[2] are managed by voluntarily formed sectors allocated with subdivisions of Annual Catch Limits (ACLs), called Annual Catch Entitlements (ACE), based on their catch history for a fixed period from 1996 to 2006 (Kitts et al. 2010; Georgianna et al. 2011). Voluntary sector means that fishermen are allowed to choose to either stay in the common pool managed by the old system or voluntarily form sectors. Sectors are free from control of DAS, area closures or trip limits, but need to implement hard limits on total allowable catch (TACs). In each sector, potential sector contributions (PSC) are calculated for each member and specie. The ACEs are allowed to be transferable within the sector and across sectors. The approach thus combines a joint liability system with an Individual Transferable Quota (ITQ) system under which each individual harvester has a right to a share of the allocation and retains any profits from using or selling that allocation.

In this paper, we use a stochastic production frontier (SPF) method to derive each fisherman's Technical Efficiency (TE) over years. We calculate both revenue-based and catch-based TE. Revenue-based TE is derived using revenue as the dependent variable in the SPF model, while catch-based TE uses catch as the dependent variable. We find that the industry's average revenue-based TE due to the new policy implementation increases by 14.62%. The increase occurs possibly through three channels. One is due to a stock effect. Since the sector management sets the limit of annual catch, the total catch decreases and thus fish stock is expected to increase. With higher fish stock level, the input needed for the same amount of output decreases, then productivity increases. The second channel is

[2] The nine allocated groundfish species include American plaice (*Hippoglossoides platessoides*), cod (*Gadus morhua*), haddock (*Melanogrammus aeglefinus*), pollock (*Pollachius virens*), redfish (*Sebastes fasciatus*), white hake (*Urophycistenuis*), winter flounder (*Pseudopleuronectes americanus*), witch flounder (*Glyptocephalus cynoglossus*), and yellowtail flounder (*Limanda ferruginea*). The four non-allocated species are halibut (*Hippoglossus hippoglossus*), ocean pout (*Zoarces americanus*), windowpane flounder (*Scophthalmus aquosus*), and wolfish (*Anarhichas lupus*).

through a price effect. Due to the new management, supply could decrease and then impact the prices. If we compute revenue-based TE, the change of TE could be driven by the price change. The third channel is through management benefit and behavioral change, and we call it a sector effect. It is possible that the voluntary sectors can promote information sharing and fishing effort optimization. Hypothetically they are more willing or able to exchange information about where and how to fish. Effort optimization can be done through ACE leasing and transferring program to rearrange fishing effort so that less efficient vessels have the option not to fish. Formed sectors can also, in theory, reduce the transaction costs of leasing and transferring ACEs. These are all examples that sector can increase productivity. However, the sector management could also reduce productivity. For example, fishermen find that comparing to the old DAS program under which time spent at sea is limited, time is not a constraint under the new sector management. So they might get loose on controlling fishing time. Consequently, productivity could decrease. Our analysis will test for the net sector effect.

We distinguish these different channels, and find that stock effect is more important than price effect and sector effect. The conclusion is inferred from comparing results from different SPF models and multiple tests. When we exclude the stock information in the SPF model, the average revenue-based TE increases statistically significantly by 14.62% as stated above, and catch-based TE increases by 8.68%. However, when we account for the stock information, the average TE increase disappears. This implies that the fish stock change is mainly responsible for the TE increase. Many studies have already shown that rights-based/quota approaches in general can be very effective to prevent fish stocks from declining[3]. This paper adds to the literature that the stock effect is the major contributor to the technical efficiency increase compared to other potential effects in the New England Groundfish fisheries.

As over-capacity is one of pressing problems of fisheries (Kirkley and Squires. 2003), it is important to examine fishermen's entry and exit behavior. In this paper, we link the TE and vessels' choice to stay, enter and exit, and find that vessels with lower TE are more willing to exit the fishery. This indicates that the new sector management is effective in improving the system efficiency.

Another issue related to TE is whether TE can determine fishermen's choice of joining the sector. The fishermen have options to choose to either stay in the common-pool or join the sector. In essence, the fishermen are choosing their fishing constraints. While common-pool is restricting effort input, sector management is restricting catch output. It is expected that the input control method can provide more incentives for the fishermen to increase their TE. Our results show that vessels with higher TE are more willing to join sectors. We argue that this is because vessels with lower TE have more room to increase their TE, so they would rather stay in the common-pool.

The rest of the paper will be organized as follows. Section 2 provides the literature background, followed by Section 3 presenting the model. After Section 4 gives the description of the data, Section 5 presents the model results and discussion and Section 6 concludes.

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[3] e.g., OECD 1997; Criddle and Macinko 2000; Matulich et al. 2001; Newell et al. 2005; Arnason 2005; Bess 2005; Pinto da Silva and Kitts 2006; Kitts et al. 2007; Deacon et al. 2008; Knapp and Murphy 2011; Costello 2012; Costello et al. 2008.

2. Literature Background

A large literature exists regarding productivity changes in fisheries (see Morrison Paul et al. (2010) for a recent survey). For example, Squires (1992) developed a framework for measuring total factor productivity in common property resource industries, with an application to the Pacific Coast trawl fishing industry. Jin et al. (2002) developed estimates of total factor productivity (TFP) change in the New England groundfish fishery accounting for stock abundance. They found that TFP in the New England groundfish fishery increased from 1964 to 1982, but declined from 1983 to 1993 mainly due to more stringent output and effort controls. Fox et al. (2003) introduced a new technique to decompose firm profits to account for fixed input, variable input prices, output prices and productivity. Using this new method, they examined the productivity change due to regulatory change. Walden et al. (2012) examined the productivity change in the Mid-Atlantic surfclam and ocean quahog fishery under ITQ management. They found that vessel productivity increased immediately after ITQ implementation, but the gains were not sustained for multiple reasons.

There are two primary methods that have been used to measure productivity (Felthoven and Morrison 2004). Under the first approach, traditional production functions are estimated and productivity indices are constructed. This approach requires aggregate indices of inputs and outputs to be constructed, with input and output prices used to construct these aggregate measures (see, e.g., Squires (1992), Jin et al. (2002), Walden et al. 2012)). Such an approach is often difficult to implement, though, because input price data are limited. The second approach seeks to estimate more direct shifts in the production technology. These can be based on primal measures (using input and output data) or dual measures (using, for example, cost or revenue functions – see Morrison Paul et al. 2010). These measures can seek to estimate shifts in either the average production function or the production frontier (Alauddin et al. 1993). Estimates of average production functions typically employ econometric estimation, while frontier analysis can be based on programming methods (e.g., Data Envelopment Analysis (DEA)) or econometric estimation (stochastic production frontiers – Tingley et al. 2005, Kumbhakar and Wang 2010). In addition, there are alternative but complementary means of estimating productivity impacts (Alauddin et al. 1993; Morrison Paul et al. 2010).

3. Methodology

In this study, we follow Battese and Coelli (1988) to use the stochastic production frontier (SPF) to estimate the productivity impact of the New England sectors. For our specific problem, a general SPF production model for the fishery can be written as:

$$y_{it} = y_{it}^{*} e^{-u_{ik}}\,, \;\; u_{ik} \geq 0 \qquad (1)$$

in which y is a scalar of output, i.e. revenue or catch, and i indicates individual vessel i. While t denotes trip time, y_i* defines the production frontier, and u_{ik} measures the technical inefficiency of vessel i in year k. Note that the production frontier varies over vessels and trips (there are multiple trips for one vessel in one year), but the technical inefficiency varies only over vessels and one year. Given that u_{ik} is constrained to be always greater or equal to zero, y_{it} will be always less or equal to y_{it}*, which implies that the observed output is bounded by the frontier. In fact, $u_{ik} = -\ln\left(\frac{y_{it}}{y_{it}^{*}}\right)$ gives the percentage of output that is lost relative to production frontier. With the value of u_{ik} closer to zero, vessel i is more efficient. In addition, y_{it}* can be modeled as:

$$\ln y_{it}^{*} = f(x_{it};\ \beta) + \varepsilon_{it} \qquad (2)$$

where x_{it} is a vector of input variables, including effort level, vessel characteristics, stock information and management etc., and β is a vector of corresponding coefficients. In addition, ε_{it} is the error term. Combined with Equation 1, the model can be written as:

$$\ln y_{it} = f(x_{it};\ \beta) + \varepsilon_{it} - u_{ik},\ \ u_{ik} \geq 0 \qquad (3)$$

The error term ε_{it} is assumed to be independent and identically distributed as $N(0, \sigma_v^2)$. It is also assumed to be independent of u_{ik}. The random variable, u_{ik}, is assumed to be independent and identically distributed by the truncated normal distribution $N(0, \sigma_u^2)$ as $u_{ik} \geq 0$. Both ε_{it} and u_{ik} are assumed to be independently distributed of the input variables in the model. Estimation of this model uses the maximum likelihood method. The likelihood function can be found in Coelli (1985).

As before, e^{-u_i} measures the distance between the output for individual vessel i and its production frontier. According to Battese and Coelli (1988), the Technical Efficiency (TE) for each vessel and each year is defined as:

$$TE_{ik} = \frac{E(y_{it}|u_{ik}, x_{it})}{E(y_{it}|u_{ik}=0, x_{it})} \qquad (4)$$

Note that this definition depends on expectations. Taking Equation 3 into 4, the individual technical efficiency can also be written as:

$$TE_{ik} = E[\exp(-u_{ik})|\varepsilon_{it}] \qquad (5)$$

The appendix gives the detailed formula to calculate the individual annual TE.

4. Data

We have compiled a few datasets in order to conduct the analysis. The first is the logbook data from 2007 to 2012 for the New England groundfish fisheries. The logbook reporting is required by law since 1994. The logbook records the information of output data including weight of catch, price by species and trip, catch region by vessel, species and trip, and input data including trip length, crew size, gear type by vessel and trip and location. The second data collect information of individual characteristics, for example, vessel tonnage and vessel power. Note that all the data contain complete information of catch of New England groundfish fisheries from 2007 to 2012.

Data on stock information (John Walden)

[Figure 1]

Table 1 lists the summary statistics for different variables. We have data for 11 different types of species. Very often that one trip cannot catch all 11 types. Therefore, there are lots of zeros. For the purpose of our analysis, we aggregate the catch data by their revenue and weight. Table 1 shows that the average catch for one trip around all six years is about 5000 lbs and the trip variations are pretty large. The average revenue is $4642 per trip. Trip length could range from less than one day to 24 days. We also list the frequencies for different gear types. Among them, gear type 3 has the highest number of trips observed. Among all the trips, 69% are made by those vessels which are in the sectors in 2011. The percentage increases to 74% in 2012. But since we only have two years' data after management implementation, we do not have enough information to infer the trend. The data also show that the sector has on average 17 vessels, from minimum 1 up to 39 vessels.

[Table 1]

We notice that there are many "inactive" vessels meaning that they have very low total catch. We drop those observations whose total trip catch is less than 100 pounds and whose total trips is less than 50 times over all six years (about 6% of observations are deleted).

The fishing year for the New England Groundfish fisheries is from May 1 to April 30 of the next year. Note that the sector management was implemented on May 1, 2010. However, since our data is from Jan 1, 2007 to Dec. 31, 2012, and we only have stock information on a calendar year base, we estimate the model using the full data on a calendar year base. The total catch over the time is shown in Figure 2. The vertical line is the sector management implementation time. Every point shows the total catch for one year. After sector management, the total catch has a lower variation than before.

[Figure 2]

Correspondingly, Figure 3 plots the number of active vessel over time. This figure shows that back from 2008, the active vessel number has already started to decline. After the sector management, the active vessel number continues to drop and the decline is even faster.

[Figure 3]

5. Results and Discussions

5.1. Channels of Technical Efficiency change: stock effect, price effect and sector effect

As stated above, we follow Battese and Coelli (1988) to use a stochastic production frontier model to estimate the individual technical efficiency over years. Table 2 shows the results. The first two models do not take stock information into account. This indicates that the technical efficiency change measured in Model 1 and 2 has the influence from the stock change. The first model uses log of total revenue as the dependent variable, meaning the output is in values giving the same amount of input. The dependent variable in the second model is logged catch in weight. In fact, the TE from Model 1 captures a mixture of stock effect, sector effect and price effect, while TE from Model 2 captures only stock effect and sector effect. Model 3 and 4 take stock information into account and Model 3 uses logged revenue as dependent variable thus captures sector effect and price effect. Lastly, Model 4 only captures sector effect. For Model 3 and 4, "stock" is the annual stock, which varies across years. We use log of t and its polynomials to capture the stock effect within a year, here "t" is the t^{th} day of a year. Note that we cannot use year dummies since they could absorb away the impact that is hard to interpret. In all of these models, vessel tonnage, vessel power, crew size and trip length are measure of inputs. Except vessel power in model 1 and 3, other types of input expand the frontier as expected. And vessel power is statistically insignificant in Model 1 and 3. We also have the information of vessel length.

But since it is highly correlated with vessel tonnage, we drop the variable. Table 2 also reports the estimation of ln (σ_u^2) and ln (σ_v^2) for each model.

[Table 2]

After estimating the model, we can calculate the expected TE for each vessel over years using Equation 5 and the formula in the appendix. Figure 4 shows the distribution of TE from Model 1 for each year. Figure 5 presents the average TE over years for four models. By visually comparing the figures, we find that models without stock information can show some TE increase after program implementation, while stock information could significantly diminish the increase.

[Figure 4]

[Figure 5]

In order to statistically compare the group means, we run a set of tests. Table 3 shows the testing results. Since TE calculated from Model 1 to 4 is from 0 to 1, we make the logit transformation of TE and use ln(TE/(1-TE)) as the dependent variable. In addition, since the sector management is implemented on May 1st 2010, we drop year 2010 to avoid unclear results for 2010. Test 1 is to test whether the TE group mean after 2010 is larger than that before 2010. The variable "after" is a dummy variable, and it is equal to 1 if after 2010. The significant positive coefficient in front of "after" for Model 1 indicates that TE increases on average. However, this increase is potentially due to either stock effect, sector effect or price effect or any combinations. Model 2 removes price effect and still shows positive TE increase. We use Model 3 and 4 to remove the stock effect and find that the positive increase disappears. Model 4 clearly shows that sector effect is not the reason for TE increase. Model 3 indicates that price effect is also not the reason for TE increase, otherwise the test will show statistically significant coefficient for “after” since now TE captures both price and sector effect. These results combined imply that stock effect is a very important factor in increasing TE, while both sector and price effects are not. Therefore, the mechanism is that the new management regime impacts the fish stock, which further changes TE.

[Table 3]

Now with some information about the group means of TE, we want to decompose the group mean change to the group of sectors and group of common pool. In order to do that, we only examine the vessels that have catches for all years except 2010. For example, the vessels that exit this fishery, or vessels that only enters after 2010 won’t show up in the data for Test 2 and 3. It turns out that there are altogether 323 vessels that continuously have catches in all years except 2010. Test 2 is to test the group mean change for the 323 vessels. The results show a similar pattern as Test 1 that stock effect is an important contributor for TE increase. In Test 3, we use the group means before 2010 as the baseline, then compare the group mean between vessels in sectors and those in common pool. TE from Model 1 shows TE of the vessel group in sectors has statistically significantly increased. Other estimates show no significant effect.

Note that the differences between Model 1 and 2 or Model 3 and 4 is model 1 and 3 use logged revenue as dependent variables and 2 and 4 use logged catch, so the TE measured from Model 1 and 3 is affected by price effect. Figure 6 plots the average fish price over years and the trend is positively corrected with TE from Model 1 (Figure 4). In fact, the average fish price is also positively corrected with fish stock (Figure 1) and negatively correlated with total catch (Figure 2). This implies that it increases after the program implementation, due to the decreased total catch.

[Figure 6]

According to the results in Table 3, we calculate the TE change for four models and 3 tests when the coefficient is significant at 1% level. The results are presented in Table 4. All tests from Model 1 predict relatively high TE increase from 12.66% to 14.62%. Test 1 indicates that after program implementation, the TE mean increases by 14.62% compared to that before 2010. For those who fish every year (except 2010), the TE mean increases by 12.66%. Among those who fish every year (except 2010), TE mean of vessels in the sectors increases by 14.22% and TE mean of those in the common pool does not increase. Test 1 for model 2 predicts 8.68% TE increase after the program implementation. All other estimates either show weak or no significant effect, so there are no numbers.

[Table 4]

5.2. Heterogeneity in Technical Efficiency change

Note that the conclusion we draw above is TE change on average in the whole New England area. In this section, we will examine the heterogeneity of change in different locations and different sectors.

Table 5 shows the group-mean test results in four locations for Model 1. The SPF model is re-estimated for the subsamples in each location. These four locations are defined according to the geographic stock information (John Walden). For each location, we run three group mean tests just as we have done in Table 3. We find that the results are significant for location 1 and 3 and TE increases due to program implementation. However, we find no significant change in location 2 and 4. The reason for no increase in location 2 is due to the low observation numbers (only 1.72% of total observations). The total catch change is not big enough to affect local stock and lead to TE change. For location 4, the reason is not clear to us, and we do not have enough information to make further inference. In fact, since location 1 has 60.87% of total results, its result dominates the average TE change in the whole area as we see in Table 3.

[Table 5]

Another perspective for heterogeneous effect is heterogeneous effects for different sectors. In 2011 and 2012, there are altogether 16 sectors. So we regress logit transformation of TE on the interactions of "after" and sectors to allow for flexible effects for sectors. We use a backward selection model to search for the regression that every variable is at least significant at 1% level. Table 6 presents the selection results. We find that sector 3 and 16 persistently show significantly positive effect throughout all four models. This implies that on average, the sector effect including sector collaboration and quota trading does not increase TE, but some sectors might work very well. We find that the coefficients for the different sector effect are negatively correlated with sector size, implying that it is not the case that bigger sector size leads to a more efficient group.

[Table 6]

5.3 Entry and exit

As TE for each vessel and each year is known, it is possible for us to link the entry and exit behavior to vessel's TE. Entry is defined as that the vessel does not have catches last year but have this year. Exit means the vessel has catches last year but not this year. The vessels, which observe catches both last year and this year, are the ones that stay. First we intend to test whether the TE is different for groups of entry, exit and staying. However, we cannot directly test it since before a vessel enters, we cannot observe its TE for last year and after a vessel exits we cannot observe its TE for this year. Therefore we separate the test into two parts. In the first part, we compare the vessels which stay and those which enter the fishery. This is shown in the row of "staying vs. entry" in Table 7. Results show that for revenue models (Model 1 and 3), TE of staying vessels is higher than that of entry vessels, while catch models (Model 2 and 4) predict lower TE for staying vessels. So these results are not consistent. If comparing staying and exit vessels (shown in the row of "Staying vs. exit"), we find that TE of staying vessels is higher than that of exit vessels according to Model 1 and 3. Model 2 and 4 do not show a significant difference between staying and exit vessels. All the results combined imply that vessels making entry and exit decisions according to revenue-based TE, instead of catch-based TE.

[Table 7]

Since TE is measuring the output production given a fixed amount of input, it can be regarded as a good indicator for profitability if it is revenue-based. Thus TE can be used as an explanatory variable for making choices of whether to stay or exit the fishery. The part of logit model in Table 7 shows the results, which indicates that higher revenue-based TE will increase the probability of staying in the fishery. Consistent with the regression model, this implies that vessels make exit decisions according to the revenue-based TE.

5.4 Quota or DAS?

Besides entry and exit choices, vessels also need to make choices whether they will join the sector. They can either choose to join the sector so that they are constrained by the hard limit of catch, or they can stay in the common pool constrained by a limited entry system, especially days at sea (DAS). Thus, the vessels are choosing between quota and DAS in essence. Table 8 presents the logit model modeling vessels' choice to join the sector. This subsample only includes those vessels which have catch observations after 2010. "TE_before" is the TE for those vessels averaged over years before 2010. The results show that for all models, the higher TE before 2010, the more chances that the vessels will join the sector after 2010. The reason is not because sector can help increase TE or profitability, as we can see from Table 4 that the sector effect is not driving TE to increase on average. The possible explanation for this is that the regulation of DAS fixes the amount of fishing time which provides the incentive to increase TE. For those vessels with already very high TE, there is limited room for them to increase TE. They would rather join the sector and be managed by the quota system. For other vessels with relatively lower TE, it would be more profitable for them to stay in the common pool since they have more chances to increase their TE, and also additionally benefit from the stock effect. It is worth pointing out that there is one caveat of this model that it assumes fishermen are not forward-looking. They make their joining decisions based on their past TE, not on the future expected TE.

[Table 8]

5.5 Validation: Results for Multi-product Production Function

All the above analyses are based on SPF models. In this section, we use a Cobb-Douglas production function to validate the previous model results.

$$y_{ik} = qE_{ik}^{\theta_1}Stock_k^{\theta_2}e^{\eta_{ik}} \qquad (6)$$

In Equation (6), y_{ik} is the output in year k for vessel i. In our model, it could be in value or in weight unit. The output is a function of E_{ik} (effort level), "Stock" (stock information) and q (catchability). In this model, q is the average catchability over years and vessels. The effort input vector as usual includes vessel characteristics and trip length. In order to compare to our previous models, we run models with and without stock information. The parameters θ_1 and θ_2 allow the flexibility for contribution of effort input and stock. If we take logs to both sides, we can estimate a log-linear regression model and η_{ik} is the error term, which is assumed to be independent and identically distributed as $N(0, \sigma^2)$. So the estimated function is:

$$lny_{ik} = lnq + \theta_1 E_{ik} + \theta_2 Stock_k + \eta_{ik} \qquad (7)$$

To capture the impact of regulatory regimes, we add a dummy for "after" just like we have done for previous models to capture the differences of catchability before 2010 and after. The model becomes:

$$lny_{ik} = lnq + \theta_1 E_{ik} + \theta_2 Stock_k + \theta_3 after + \eta_{ik} \qquad (7)$$

Table 9 shows the results for multi-product production function. Again the dependent variable for Model 1 and 3 are logged revenue and for Model 2 and 4 are logged catch.

Model 3 and 4 are models without stock information. These models are run on an aggregated annual level. So the input and output are aggregated over one year for individual vessels. The results are consistent with those from the previous main model. Without stock information, coefficients for “after” are significantly positive. When adding stock information, the coefficients become insignificant, implying that stock effect is the major reason that drives the increase of catchability/productivity.

[Table 9]

6. Conclusion

In this paper, we use stochastic production frontier model to compute value-based and catch-based Technical Efficiency and then empirically test the impact of sector management on technical efficiency.

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Appendix

Battese and Coelli (1988) proves that:

$$TE_{ik} = E[\exp(-u_{ik})\,|\varepsilon_{it}] = \{\frac{1-\Phi\left[\sigma_* - \left(\frac{u_{ik}^*}{\sigma_*}\right)\right]}{1-\Phi(-u_{ik}^*/\sigma_{*)}}\}\exp\,(-u_{ik}^* + 1/2\sigma_*^2)$$

in which

$$u_{ik}^* = \frac{-\sigma_u^2\overline{e_\iota}}{\sigma_u^2 + T^{-1}\sigma_v^2}$$

$$\sigma_*^2 = \frac{\sigma_u^2\sigma_v^2}{\sigma_v^2 + T\sigma_u^2}$$

and

$$\overline{e_\iota} = T^{-1}\sum_{t=1}^{T}(\varepsilon_{it} - \mathrm{u_{ik}})$$

and Φ represents the standard normal distribution function.

Figure 1: Fish Stock Index

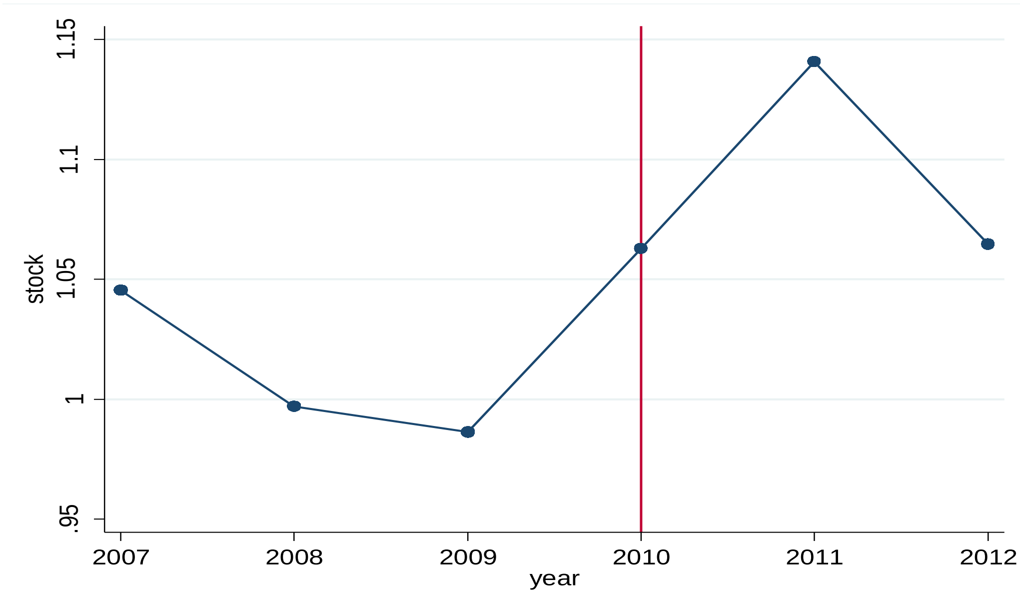

Figure 2: Total catch over years

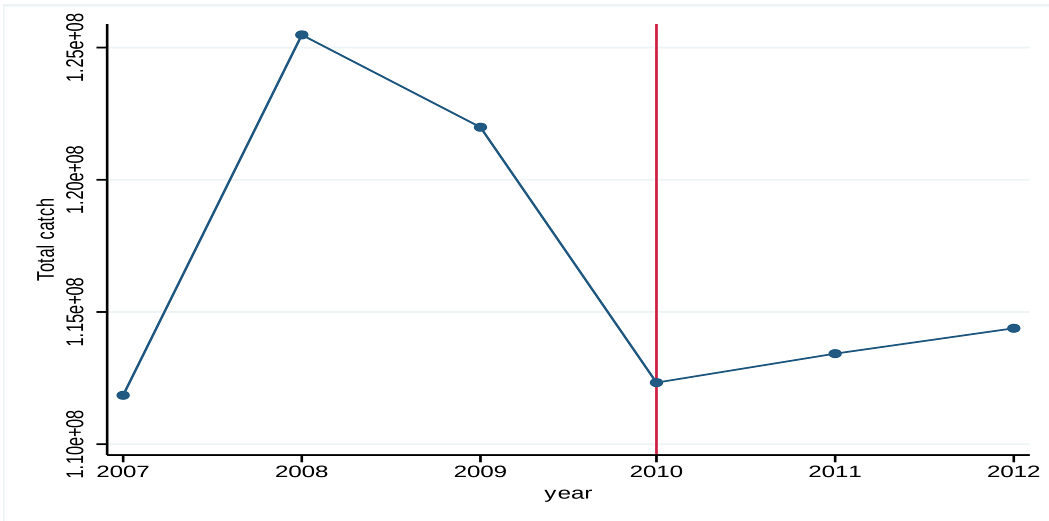

Figure 3: Vessel number over years

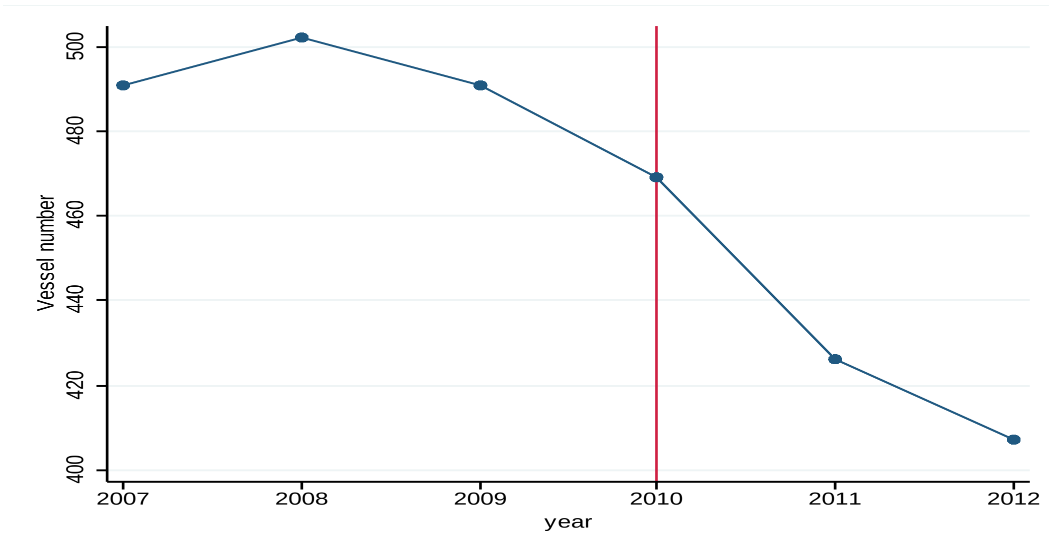

Figure 4: Distribution of TE over years from model 1

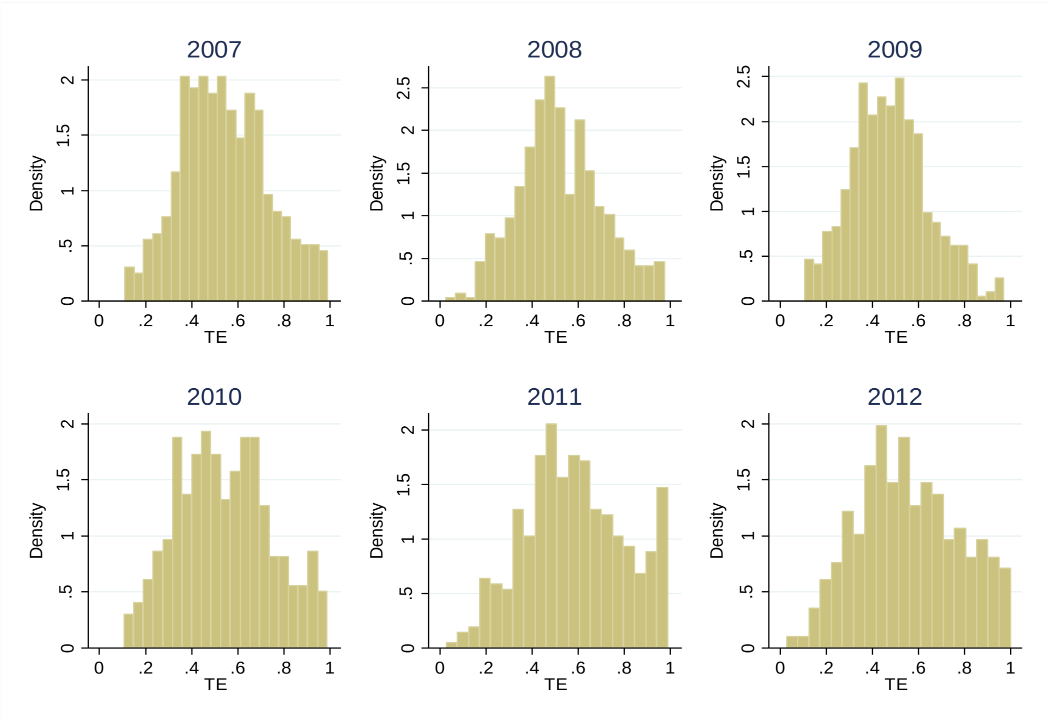

Figure 5: Average Technical Efficiency over years

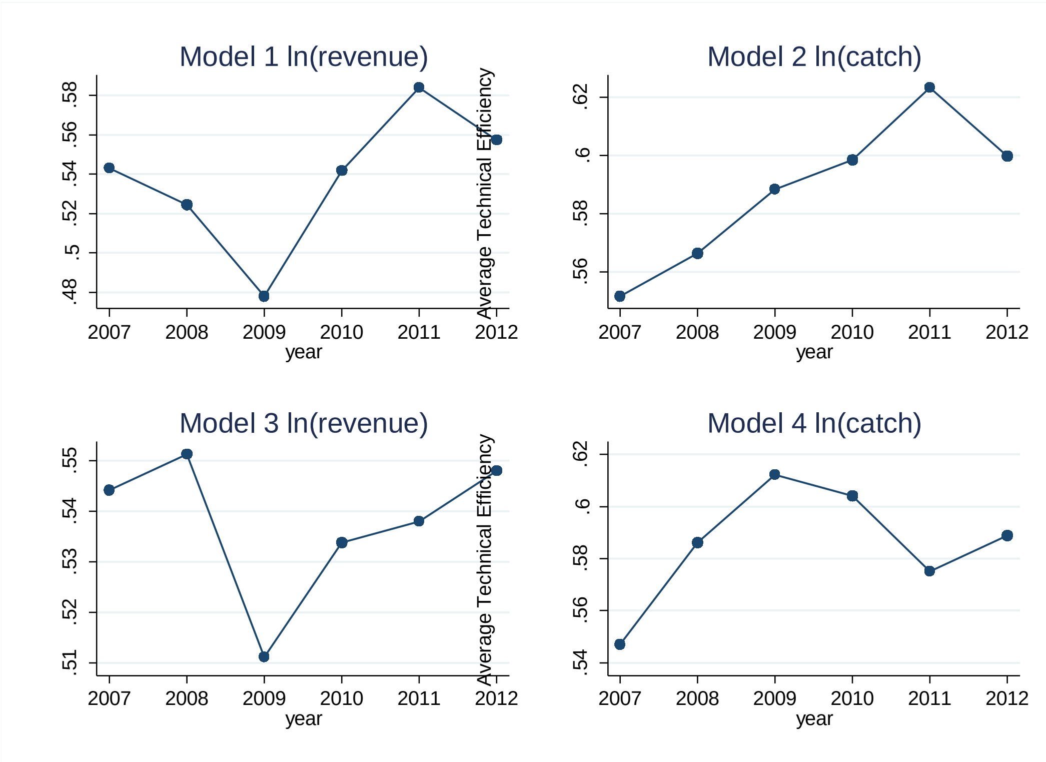

Figure 6: Fish price over years

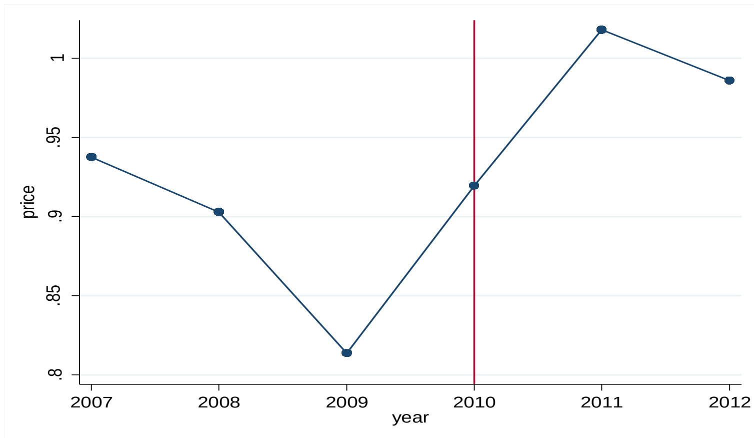

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Trip catch (lbs)	5037	13421	1	2547079
Trip catch value ($)	4642	10252	0	633912
Vessel tonnage	51	49	1	201
Vessel size (m)	51	16	9.75	107
Vessel power	410	200	1	2000
Crew number	2.75	2	1	55
Trip length (day)	0.998	1.77	0.002	23.938
Variable				
gear type 1 trip %	39%			
gear type 2 trip %	5%			
gear type 3 trip %	56%			
Vessel trips of Sectors 2011 %	69%			
Vessel trips of Sectors 2012 %	74%			
Sector size	17	12.1	1	39

Table 2: Result from the stochastic production frontier model

	Model 1 (ln(revenue))		Model 2 (ln(catch))		Model 3 (ln(revenue))		Model 4 (ln(catch))	
Frontier	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error
ln(tonnage)	0.189***	(0.003)	0.237***	(0.004)	0.188***	(0.003)	0.245***	(0.004)
ln(power)	-0.001	(0.004)	0.091***	(0.005)	-0.002	(0.003)	0.087***	(0.005)
ln(crew)	0.602***	(0.005)	0.712***	(0.007)	0.590***	(0.005)	0.710***	(0.007)
ln(trip len)	0.653***	(0.002)	0.577***	(0.003)	0.649***	(0.002)	0.598***	(0.003)
Grear 2	0.134***	(0.010)	0.334***	(0.013)	0.124***	(0.010)	0.350***	(0.013)
Gear 3	-0.073***	(0.005)	0.301***	(0.006)	-0.072***	(0.005)	0.273***	(0.006)
Ln(Stock)					1.090***	(0.038)	1.009***	(0.047)
lnt					0.366***	(0.056)	-0.358***	(0.071)
lnt^2					-0.191***	(0.031)	0.169***	(0.039)
lnt^3					0.037***	(0.007)	-0.012***	(0.008)
lnt^4					-0.002***	(0.001)	-0.001***	(0.001)
cons	7.672***	(0.021)	6.576***	(0.028)	6.359***	(0.056)	5.603***	(0.070)
$\ln(\sigma_u^2)$	-0.324***	(0.011)	-0.711***	(0.037)	-0.306***	(0.010)	-0.676***	(0.033)
$\ln(\sigma_v^2)$	-1.303***	(0.009)	-0.470***	(0.011)	-1.330***	(0.009)	-0.527***	(0.010)
obs:	140646		140652		140646		140652	
Effect captured in TE	Stock effect+Sector effect+Price effect		Stock effect +Sector effect		Sector effect +Price effect		Sector effect	

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 3: Group mean testing

		Model 1		Model 2		Model 3		Model 4	
	Ln (TE/(1-TE))	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Test 1	after	0.312***	(0.044)	0.219***	(0.053)	0.045	(0.039)	0.034	(0.053)
	cons	0.099***	(0.027)	0.380***	(0.031)	0.178***	(0.023)	0.447***	(0.032)
Test 2	after	0.288***	(0.053)	0.103*	(0.061)	0.012	(0.046)	-0.095	(0.061)
	cons	0.206***	(0.034)	0.464***	(0.039)	0.280***	(0.029)	0.527***	(0.039)
Test 3	after*sector	0.353***	(0.059)	0.108	(0.068)	0.070	(0.051)	-0.108	(0.068)
	after*common	0.122	(0.084)	0.090	(0.097)	-0.139*	(0.073)	-0.062	(0.098)
	cons	0.206***	(0.034)	0.464***	(0.039)	0.280***	(0.029)	0.527***	(0.039)

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 4: Technical Efficiency change

	Model 1	Model 2	Model 3	Model 4
Test 1	14.62%	8.68%	--	--
Test 2	12.66%	--	--	--
Test 3	14.22%	--	--	--
Effect captured in TE	Stock effect +Sector effect +Price effect	Stock effect +Sector effect	Sector effect +Price effect	Sector effect

Table 5: Group mean testing in different locations

		Model 1							
		Location 1		Location 2		Location 3		Location 4	
	Ln (TE/(1-TE))	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Test 1	after	0.269***	(0.054)	0.173*	(0.104)	0.446***	(0.066)	0.032	(0.077)
	cons	0.333***	(0.032)	0.012	(0.059)	0.248***	(0.041)	0.045	(0.038)
Test 2	after	0.252***	(0.062)	0.086	(0.122)	0.427***	(0.075)	0.068	(0.090)
	cons	0.412***	(0.039)	0.040	(0.071)	0.360***	(0.048)	0.080*	(0.047)
Test 3	after*sector	0.288***	(0.063)			0.387***	(0.089)	-0.007	(0.142)
	after*common	-0.481**	(0.226)			0.486***	(0.103)	0.105	(0.105)
	cons	0.412***	(0.039)			0.360***	(0.048)	0.080*	(0.047)

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 6: Heterogeneity in Sector Impact

Model 1			Model 2			Model 3			Model 4		
	Coef.	Std. err.		Coef.	Std. err.		Coef.	Std. err.		Coef.	Std. err.
after*s3	0.980***	(0.129)	after*s2	1.381***	(0.213)	after*s3	0.653***	(0.111)	after*s2	1.327***	(0.199)
after*s6	0.957***	(0.360)	after*s3	0.829***	(0.146)	after*s9	0.384***	(0.112)	after*s3	0.611***	(0.147)
after*s9	0.698***	(0.130)	after*s10	-0.624***	(0.152)	after*s10	-0.334***	(0.116)	after*s4	-0.655***	(0.211)
after*s13	0.959***	(0.194)	after*s13	0.666***	(0.220)	after*s13	0.656***	(0.168)	after*s7	-0.571***	(0.201)
after*s16	2.069***	(0.360)	after*s16	1.442***	(0.409)	after*s16	1.429***	(0.311)	after*s10	-0.755***	(0.153)
cons	0.225***	(0.027)	cons	0.449***	(0.031)	cons	0.238***	(0.023)	after*s16	1.244***	(0.411)
									cons	0.480***	(0.031)
Corr with sector size		-0.647			-0.587			-0.765			-0.248

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 7: Entry Exit and Technical Efficiency

	Model 1		Model 2		Model 3		Model 4	
	Regression Model							
Ln (TE/(1-TE))	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Staying	0.265**	(0.116)	-0.353***	(0.135)	0.239**	(0.099)	-0.257*	(0.135)
cons	-0.049	(0.113)	0.837***	(0.131)	-0.042	(0.097)	0.753***	(0.132)
Staying	0.324***	(0.089)	0.155	(0.101)	0.284***	(0.076)	0.059	(0.101)
cons	-0.028	(0.085)	0.316***	(0.097)	-0.047	(0.073)	0.379***	(0.097)
	Logit Model							
Staying	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
TE	1.724***	(0.453)	0.679*	(0.395)	1.854***	(0.480)	0.263	(0.395)
cons	1.562***	(0.239)	2.070***	(0.236)	1.500***	(0.251)	2.306***	(0.240)

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 8: Quota Vs. DAS

	Model 1		Model 2		Model 3		Model 4	
	Logit Model							
sector	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
TE	4.667	(0.088)	0.763	(0.060)	4.882	(0.089)	0.455	(0.061)
cons	-1.340	(0.045)	0.627	(0.037)	-1.549	(0.048)	0.802	(0.039)

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 9: Multi-product Production Function

	Model 1 (ln(revenue))		Model 2 (ln(catch))		Model 3 (ln(revenue))		Model 4 (ln(catch))	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
ln(tonnage)	0.187***	0.013	0.199***	0.018	0.187***	0.013	0.199***	0.018
ln(power)	0.075***	0.019	0.150***	0.026	0.074***	0.019	0.149***	0.026
ln(crew)	0.317***	0.014	0.402***	0.018	0.318***	0.013	0.402***	0.018
ln(trip len)	0.875***	0.013	0.809	0.017	0.878***	0.013	0.811***	0.017
ln(stock)					1.730***	0.246	0.869	0.332
after	0.133***	0.017	0.088***	0.023	0.001	0.025	0.022	0.034
Gear 2	0.211***	0.038	0.190***	0.051	0.212***	0.038	0.191***	0.051
Gear3	-0.062***	0.021	0.319***	0.028	-0.064***	0.021	0.318***	0.028
cons	6.169***	0.112	5.423***	0.150	6.135***	0.111	5.406***	0.150
Obs.	2787		2787		2787		2787	
R-squared	0.90		0.84		0.90		0.84	

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.