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ABSTRACT

This paper investigates changes in the total factor productivity (TFP) and identifies the main sources of TFP growth following the adoption of an individual fishing quota (IFQ) program in the Gulf of Mexico red snapper commercial fishery. Utilizing an unbalanced panel of 722 vertical line vessels we built Malmquist indices derived from an output-oriented stochastic distance frontier. The study shows that the IFQ program had a positive impact on the productivity of the fleet and that most of the productivity gains were due to improvements in technical efficiency. The study also finds that changes in technical efficiency were time variant suggesting that the exit of the less efficient vessels and easing of command and control regulations such as trip limits and short fishing seasons were responsible for most of these gains. Changes in the exploitable biomass of red snapper were found to have a moderate impact on productivity growth whereas the impact of technological progress was minimal.

Key words: Productivity change, individual fishing quotas, stochastic frontier distance function.

JEL Codes: D24, Q22.

INTRODUCTION

Capture fisheries around world are increasingly being managed with individual fishing quotas (IFQs). Today, about one-quarter of the global marine harvest is managed with IFQs (Arnason, 2012). Under an IFQ program, fishers are assigned exclusive harvesting privileges based on a share of the quota which is expected to encourage the balancing of the harvesting capacity with the productivity of fish stocks. Fishers are not only expected to use capital and labor more wisely, but also are expected to adjust the scale and scope of their operations by trading shares.

The rapid proliferation of IFQs has resulted in voluminous literature assessing their biological, economic and social performance. Perusal of this large body of work suggests that IFQs with hard total allowable catch (TAC) have had largely positive biological impacts on target species (e.g., catches below the TAC) but had unknown or mixed impacts on by-catch or incidental species and the overall ecosystem (Branch, 2009; Essington, 2010). Costello et al. (2008) concluded that the adoption of IFQs reduced the likelihood of stock collapse, whereas Heal and Schlenker (2008) reported that the IFQs have contributed to higher catches. However, this latter claim has been challenged by Nowlis and van Benthem (2012), who argued that some of the observed catch gains may be also due to improved catch reporting systems often concurrently put in place with IFQs. The extant economic literature has generally viewed IFQs favorably highlighting how promoting a sound incentive structure leads to reductions in fishing effort, mitigation of derby fishing conditions, prolonged fishing seasons, higher prices, lower harvesting costs, improved fish handling and quality, wealth creation, and improved safety and resource stewardship (Squires et al. 1995; Squires et al. 1998; NRC 1999; Sutinen 1999; Nostbakken et al. 2011; Brinson and Thunberg 2013). However, some of the anticipated benefits such as capital savings were slower to materialize because of the non-malleability of capital and uncertainty over the worth of the quota shares (Weninger and Just 1997; Vestergaard et al. 2005; Nostbakken et al. 2011). In contrast, most of the literature dealing with the social impacts of IFQs has been critical focusing on fairness and equity concerns (NRC 1999; Eythórsson 2000; Olson 2011). It has described how the distribution and concentration of quota resulted in the fewer at sea and on-land employment opportunities, disadvantaged small fishing communities, lower wages and bargaining power of crew and captains class divisions and financial hardships for prospective fishers.

One important but less studied anticipated outcome of enacting IFQs has to do with quantification of productivity gains, where these gains refer to the ability of fishing firms to harvest of more fish with the same amount of inputs or harvest the same amount of fish using fewer inputs (Walden et al. 2014). Theoretically, by ameliorating derby fishing behavior, fishers can dedicate more time to harvesting, processing and marketing their landings more proficiently. They can also spend more time developing fishing practices that improve their catch composition and make better use of their capital, labor and other inputs. Additional productivity gains may be achieved by excessing redundant capital and labor by transferring of quota from less to more efficient vessels (Walden et al. 2014).

The purpose of this study is to investigate the impact of the Gulf of Mexico (GOM) red snapper IFQ program on the total factor productivity (TFP) of the vertical line fleet. We also decompose the sources of TFP growth into technological progress and changes in technical efficiency and stock change using a Malmquist Index (MI) derived from an output-oriented stochastic distance frontier (OSDF). The used of OSDF has been favored when studying fisheries productivity since the method allows for the random and multi-product and factor nature of the harvesting process (Orea et al. 2005; Felthoven et al. 2009; Solís et al. 2014a; among others). The red snapper fishery was selected as a case study because is one the most valuable commercial fisheries in the GOM and recently began being managed with IFQs.

The rest of this article is organized as follows. The next section presents an overview of the management history of the red snapper fishery, followed by a review of the literature on fisheries productivity. Next, we describe the data and methods and introduce the empirical model. Then, we present, analyze and discuss key results. The article concludes with a summary of the main findings and policy implications.

OVERVIEW OF THE MANAGEMENT HISTORY

The red snapper fishery has a long and complex management history. Federal management began with the implementation of the GOM Reef Fish fishery management plan (FMP) in 1984 which established minimum size limits. In response to declining stocks, the GOM Fishery Management Council (Council) established a TAC in 1990, which led to premature fishery closures. For example, in 1995 the fishing season only lasted 52 days whereas 5 years earlier the fishing season was open year round (Waters 2001; Strelcheck and Hood 2007).

In early nineties, the deteriorating condition of the resource and the intensification of derby fishing conditions led the Council to lower the TAC and subsequently establish a moratorium on reef-fish permits, tiered trips limits (200 and 2000 lbs.), and red snapper endorsements. In 1995, a new stock assessment suggested that the stock was in better condition than previously believed which allowed the Council to raise the TAC. In 1996, the Council split the TAC into spring and fall fishing seasons. The fall season was included to accommodate larger landings but also to mitigate the market gluts caused by derby fishing behavior during the spring season (Waters 2001). Unfortunately, the larger quota and tiered trip limits and fishing seasons failed to slow down the fishery (Hood et al. 2007).

To address the adverse socio-economic impacts of progressively shorter fishing seasons, the Council limited the fishers to fish during the first 15 days of each month (later on only 10 days) or until the quota was reached. It also established a permanent, two tiered red snapper endorsement system made up of Class 1 and Class 2 licenses, which allowed fishers to harvest 2,000 and 200 lbs. trip limit, respectively.

The failure of command and control management measures to restore the biological and economic viability of the fishery, led the Council implemented an IFQ program for the commercial red snapper fishery on January 1, 2007. The intent of the program was to redress the problems associated with overcapacity and derby fishing conditions by assigning fishers with secure and tradable harvesting privileges which mitigated the incentives to invest in redundant fishing capital and to harvest as fast as possible to preempt the harvesting activities of other fishers.

Since its adoption of the IFQ program significant structural changes have taken place. Agar et al. (2014) conducted a review of the first five years of the IFQ program. This 5-year review found that there were significant capital and labor savings in the fishery. Five-year pre- and post-IFQ averages showed that the fleet size fell by 29% and that the number of days fished and crew-days declined by 4% and 6%, respectively. However, Solís et al. (2014a) estimated that additional savings were required to achieve an economically optimal fleet configuration. They estimated that one-fifth of the existing fleet could harvest the entire quota. Improvements in the technical efficiency of the remaining fleet were also documented (Solís et al. 2014b). Share and lease prices increased significantly suggesting that the IFQ program had contributed to the profitability of the fishery. In addition, there were no quota overages since the IFQ program began (Agar et al. 2014). However, the stock remains overfished, although is not undergoing overfishing. The review also found that the IFQ program was successful in mitigating the race to fish behavior. The fishing season expanded from 5-year pre-IFQ average season of 109 days to a year-round season which allowed fishers to harvest, process, and market their catch more efficiently (Agar et al. 2014). Fishers began taking longer fishing trips and diversifying the composition of their output mix by targeting more vermilion snapper and red grouper (Figure 1). Cursory review of single factor productivity indices depicted in Figure 2 shows important productivity gains in the harvest of vermilion snapper and red grouper and minor gains in the harvest of red snapper following the IFQ program. However, these partial metrics fail to account for confounding effects such as changes in resource and market conditions which may provide offer a distorted view of the productivity gains observed. This study sheds light on this key issue by rigorously measuring productivity changes before and after the adoption of the IFQ program.

LITERATURE REVIEW

Productivity is a key economic indicator used to analyze the performance of production units (Färe et al. 2008). In a fisheries setting, productivity captures the relationship between the quantity of fish produced (harvested) and the amount of inputs used to harvest fish. Fishing fleets became more productive when fishing vessels catch the same amount of fish with fewer inputs. Because of the multispecies and stochastic nature of the harvesting process different approaches have employed to measure TFP growth in commercial fisheries. Table 1 presents a summary of recent empirical studies in this area of research.

The most straightforward approach is to construct productivity indexes (PIs) using index numbers, such as, Laspeyres, Lowe, Fisher, Paasche, and Törnqvist indexes. PIs have become very popular in the literature because they are easy to calculate and require less data when compare to other approaches. In addition, PIs can be interpreted in the same fashion than the one described for the single-output/single-input case (Coelli et al. 2005).

Using PIs, Squires (1992) extended the standard TFP measurement by including stock abundance. He argued that industries that harvest common-pool resources need to account for the unpriced contributions from fish stocks to obtain unbiased measurements of productivity or technical progress. In his empirical work, he used a biomass-adjusted Törnqvist index to estimate TFP changes in the Pacific coast trawl fishery. Following Squires (1992), Jin et al. (2002)

estimated changes in TFP for the New England groundfish fishery. Both, Squires (1992) and Jin et al. (2002) concluded that productivity changes are sensitive to stock abundance; thus the omission of stock abundance in the estimation of TFP may produce biased estimates. Stephan and Vieira (2013) used a stock corrected Fisher index to study productivity trends for key Commonwealth fisheries in Australia. The authors found an increasing trend in productivity especially after the introduction of a buyback program. Also using index numbers Fox et al. (2003, 2006) decomposed profit and productivity in the British Columbia halibut fishery. Fox et al. (2003) found that individual harvesting rights had a positive effect in the industry performance mainly because an increase in output prices. Walden (2013) and Walden and Kitts (2014) found that the economic well-being of the northeast US multispecies trawl fleet increased after the implementation of catch shares. Other productivity studies using PIs include Islam (2011) who, studied fisheries in coast of Peninsular Malaysia, Eggert et al. (2013), who compared the Icelandic, Norwegian and Swedish fisheries, and Hannesson (2007) and Hannesson et al. (2010), who assessed the Lofoten fishery in Norway. One of the key drawbacks of PI approach is that by aggregating inputs and outputs, technological interdependences cannot be assessed.

An alternative framework to measure TFP is the use of frontier methods. These methods are based on the notion of a 'best practice' frontier which depicts the boundary of the production possibility set. Frontier methods assess productivity changes by measuring how the distance between the firms' production frontier and the 'best practice' frontier vary over time. Frontier analyses can be estimated using parametric and non-parametric techniques. Non-parametric methods employ mathematical programming techniques, such as data envelopment analysis (DEA), to estimate the frontier. Conversely, parametric methods require imposing a specific functional form and use econometric techniques to estimate production, cost, revenue or distance functions (Coelli et al. 2005).

Within the frontier methods, DEA has been a popular technique to measure TFP in fisheries. Most DEA studies have used the MI to estimate and decompose productivity changes. Walden et al. (2012) indicates that MI is advantageous for the study productivity in this economic sector for two main reasons. First, MI can be estimated using quantities rather than prices. This feature is important because of the lack or limited availability of price and cost data for most fisheries. Second, MI preserves the symmetry in output mix, which is especially important when studying multi-species fisheries. Under a multi-output framework, vessels can have zero valued outputs for one or more outputs and the MI can ensure that those outputs stay zero.

Recent TFP studies using DEA in fishing include Hoff (2006), Squires et al. (2008), Oliveira et al. (2009), Kim et al. (2012) and Walden et al. (2012). Summaries of these papers can be found in Table 1. A relevant study for our work is the paper by Walden et al. (2012) who studied the impact of IFQ on the productivity Mid-Atlantic surf clam and ocean quahog fishery. Walden et al. (2012) found productivity gains for the fleet immediately following implementation of the IFQ program. However, these productivity gains were not sustained over time. The authors surmised that these results were driven by spatial changes in biomass and regulatory access restrictions to the best fishing grounds.

Despite the popularity of the DEA method, Orea et al. (2005) and Felthoven et al. (2009) warn that the deterministic nature of this methodology fails to account for the stochastic nature of commercial fishing operations. Fluctuations in stock abudance, market instablity, and severe weather inject considerable uncertainty into the harvesting process (Symes and Phillipson, 2009). Hence, recent studies have argued that the stochastic frontier analysis (SFA) method is better suited to study harvesting processes because it allow for the inclusion of 'noise' in the estimation of the model. In addition, the parametric nature of the SFA generates valuable information on the relationship between harvest levels and control variables, e.g., factors of production, regulatory conditions, environmental variables, etc.

Very few studies have used SFA to measure TFP in fisheries. Among the few studies found, Felthoven et al. (2009) measured productivity changes for the Alaskan Pollock fishery before and after the introduction of an exclusive harvesting privileges program. Using a quadratic transformation function, Felthoven et al. (2009) found an increase in productivity over time which is explained by the changes in regulatory conditions, as well as by changes in climatic conditions, bycatch levels and stock abundance. However, this study does not explicitly decompose the TFP growth into its components. Conversely, O'Donell (2013) implemented a Bayesian framework to compute and decompose TFP changes in the Australian northern prawn fishery using the Färe-Primont index. This framework allows for inferences to be made about productivity when little data is available. However, the estimation of this model is complex and computationally demanding.

The current study adds to the literature by estimating and decomposing productivity changes explicitly accounting for stock abundance. In addition, we estimate MI using a multi-output/multi-input stochastic distance frontier (SDF) model. To the best of our knowledge, this is the first study deriving MI from a SDF in a multispecies fishery setting.[1]

METHODS

In this study we estimate and decompose productivity changes using a Malmquist Index (MI) in the GOM red snapper fishery from 2001 to 2012 (six years before and after the implementation of the IFQ program). MI is an index-based approach that relies on radial distance functions. To estimate our model we utilize the SDF framework, and in the following subsections describe in details the MI and the SDF model.

Malmquist Productivity Index and the Decomposition of TFP

Coelli (2000) indicates that in a multi-output/multi-input environment, distance functions offer a more accurate representation of a production technology than single-output models. Distance function can be derived using input or output orientations. Orea et al. (2005) state that due to the quasi-fixed nature of fishing capital, output-oriented models are preferable when analyzing production processes in this industry. Specifically, the output distance function (ODF) measures the maximum amount by which an output vector can be proportionally expanded and still be producible with a given input vector. Algebraically, ODF is depicted as:

$$D_o(x,y) = \min\{\theta > 0 : (y/\theta) \in P(x)\} \quad \textbf{(1)}$$

where $P(x)$ is the set of feasible output vectors obtainable from the input vector x and $D_o(x,y)$ represents the output-oriented distance to the production frontier. If $D_o(x,y) \leq 1$, then (x,y) belongs to $P(x)$. Additionally, if $D_o(x,y) = 1$, then y is located on the outer boundary of $P(x)$ (Coelli 2002, Perelman and Santin 2011, Brümmer et al 2002).

[1] Previous studies measuring MI in fishing have used DEA (Table 1).

Within this framework, changes in TFP (or MI) for vessel *i* between two consecutive time periods (*t* and *t+1*) based on year *t* technology is defined as:

$$MI_{oi}^{t} = \frac{D_o^t(x_i^{t+1}, y_i^{t+1})}{D_o^t(x_i^t, y_i^t)} \tag{2}$$

In other words, MI compares the efficiency of vessels in period *t+1* with respect to their efficiency in the previous period assuming the same technology (*i.e.*, the frontier in period *t*). Thus, a numerator larger than the denominator (MI greater that one) suggests an increase in TFP.

To account for resource abundance we incorporate the stock size in the calculation of the MI. Hence, a stock corrected MI can be computed as:

$$MI_{oi}(T_t, S_t) = \frac{D_o^t(x_i^{t+1}, y_i^{t+1}; S_t)}{D_o^t(x_i^t, y_i^t; S_t)} \tag{3}$$

where T_t is the state of the technology in period *t* and S_t is a stock abundance measure in period *t.*

To analyze the factors affecting productivity changes we further decompose TFP growth (changes in MI) into three components: technical change (TC), efficiency change (EC) and stock change (SC).[2] TC identifies changes in the technology (shifts in the frontier not related to changes in stock abundance), while EC measure efficiency changes (movement toward the frontier) and SC identifies shifts in the frontier due to changes in stock abundance.

To decompose TFP we first multiply and divide equation 3 by $D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_{t+1})$:

$$MI_{oi}(T_t, S_t) = \frac{D_o^t(x_i^{t+1}, y_i^{t+1}; S_t)}{D_o^t(x_i^t, y_i^t; S_t)} \cdot \frac{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_{t+1})}{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_{t+1})}$$

[2] Previous studies have only assessed the effect of stock abundance on production levels (Squires 1992; Jin et al. 2002; Felthoven et al. 2009). However, in this study we explicitly evaluate the influence of stock abundance into the vessel's changes of productivity levels by including stock abundance as an additional component of TFP. Due to data limitations we only include the effect of the target species (red snapper) in the empirical estimation and decomposition of the MI.

$$MI_{oi}(T_t, S_t) = \frac{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_{t+1})}{D_o^t(x_i^t, y_i^t; S_t)} \cdot \frac{D_o^t(x_i^{t+1}, y_i^{t+1}; S_t)}{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_{t+1})} = EC \cdot \frac{D_o^t(x_i^{t+1}, y_i^{t+1}; S_t)}{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_{t+1})}$$

(4)

Then, we multiply and divide equation 4 by $D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_t)$:

$$MI_{oi}(T_t, S_t) = EC \cdot \frac{D_o^t(x_i^{t+1}, y_i^{t+1}; S_t)}{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_{t+1})} \cdot \frac{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_t)}{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_t)} \rightarrow$$

$$MI_{oi}(T_t, S_t) = EC \cdot \frac{D_o^t(x_i^{t+1}, y_i^{t+1}; S_t)}{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_t)} \cdot \frac{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_t)}{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_{t+1})} = EC \cdot TC \cdot SC$$

(5)

To assist with the interpretation of the MI and its decomposition, we offer a graphical depiction of the harvest to two species in a deterministic setting (Figure 3).[3] MI is calculated by dividing $D_o^t(x_i^{t+1}, y_i^{t+1}; S_t)$ or OB/OD by $D_o^t(x_i^t, y_i^t; S_t)$ or OA/OC. This overall efficiency metric is measured assuming the technology and stock sizes are the same during the two time periods. Thus, if the efficiency metric for a vessel in period *t+1* is greater than in period *t* then that vessel is more productive.

Now, let's decompose the MI into its three components. EC allows us to compare the efficiency of a vessel in the period *t* and in *t+1*. Specifically, EC measures whether a vessel get closer to (or further from) the best-practice frontier. If the efficiency for a vessel in the period *t+1* is greater than in the period *t* then the efficiency change is positive and the estimated ratio will be greater than one. EC is simply calculated by dividing $D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_{t+1})$ or OB/OF by $D_o^t(x_i^t, y_i^t; S_t)$ or OA/OC. TC measures by how much the production possibility set shifts between two time periods and can be computed by dividing $D_o^t(x_i^{t+1}, y_i^{t+1}; S_t)$ or OB/OD and $D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_t)$. Alternatively, TC equals OB/OE:

$$TC = \frac{OB}{OD} / \frac{OB}{OE} = \frac{OE}{OD}$$

[3] In the following subsection we will introduce random shocks in the estimation of the production distance frontier.

(6)

In other words, if the production possibility set move upwards the technological change will be positive, *i.e.*, a ratio greater than one.

Finally, SC measures how the production possibility set will shift if the stock changes, holding all other factors constant. Explicitly, SC can be calculated by dividing $D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_t)$ or OB/OE by $D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_{t+1})$ or OB/OF. Mathematically,

$$SC = \frac{OB}{OE} / \frac{OB}{OF} = \frac{OF}{OE}$$

(7)

It is important to clarify that the selection of the benchmark technology, time-periods *t* or *t+1*, is arbitrary. Thus, conventionally, MI has been defined as the geometric mean (GM) of these two time-periods (Lovell, 2003). In doing so, MI is estimated as MI_{oi} instead $MI_{oi}(T_t)$. The main implication of this approach is that the TC is also calculated as a GM.[4] Since our application also includes SC, this component needs to be estimated as a GM as well. Consequently, in this study we will estimate MI_{oi} instead $MI_{oi}(T_t, S_t)$ which is in line with the productivity literature (Walden et al. 2012; Squires et al. 2008; among others). TC and SC are now calculated as:

$$TC = \left[\frac{D_o^t(x_i^{t+1}, y_i^{t+1}; S_t)}{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_t)} \cdot \frac{D_o^t(x_i^t, y_i^t; S_t)}{D_o^{t+1}(x_i^t, y_i^t; S_t)}\right]^{0.5}$$

(8)

$$SC = \left[\frac{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_t)}{D_o^{t+1}(x_i^{t+1}, y_i^{t+1}; S_{t+1})} \cdot \frac{D_o^t(x_i^t, y_i^t; S_t)}{D_o^t(x_i^t, y_i^t; S_{t+1})}\right]^{0.5}$$

(9)

Stochastic Distance Frontier

[4] Using the $MI_{oi}(T_t)$ framework TC is calculated as $D_o^t(x_i^{t+1}, y_i^{t+1})/D_o^{t+1}(x_i^{t+1}, y_i^{t+1})$ whereas in the MI_{oi} framework TC is equal to $\left(\frac{D_o^t(x_i^{t+1}, y_i^{t+1})}{D_o^{t+1}(x_i^{t+1}, y_i^{t+1})} \cdot \frac{D_o^t(x_i^t, y_i^t)}{D_o^{t+1}(x_i^t, y_i^t)}\right)^{0.5}$ (Fuentes et al. 2001).

We model the ODF using a translog (TL) functional form. Coelli and Perelman (1999) show that TL functional form is a good approximation to the true distance function and is sufficiently flexible to allow for the imposition of desirable properties such as homogeneity and symmetry. A TL ODF model can be described as:

$$
\begin{aligned}
lnD_{oi} = \beta_0 &+ \sum_{m=1}^{M} \beta_m lny_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn} lny_{mi} lny_{ni} + \sum_{k=1}^{K} \beta_k lnx_{ki} \\
&+ \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} lnx_{ki} lnx_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M} \beta_{km} lnx_{ki} lny_{mi} + \sum_{m=1}^{M} \beta_{tm} t lny_{mi} \\
&+ \sum_{k=1}^{K} \beta_{tk} t lnx_{ki} + \sum_{j}^{J} \theta_j D_j + \sum_{h}^{H} \theta_h lnC_h
\end{aligned}
\qquad (\mathbf{10})
$$

where D_{oi} denotes the output distance function measure, y_{mi} is the vector of outputs, x_{ki} is the vector of inputs, D_j is a vector of dummy variables and C_h is a vector of control variables . We allow the rate of technical change to be non-constant and non-neutral by interacting time (t) with the first-order coefficients for inputs and outputs, which allows us to identify technical change over time. Vessels are indexed by subscript i.

To satisfy the necessary conditions for a well-behaved ODF we normalize the function by an arbitrary output and we impose symmetry by setting $\beta_{mn} = \beta_{nm}$ and $\beta_{kl} = \beta_{lk}$ (Coelli and Perelman, 1999). After imposing these restrictions, defining the distance from each observation to the frontier as inefficiency (*i.e.*, $ln\mathrm{D}_{oi} = -u_i$) and adding a random noise variable (v_i) into the model (Equation 10) an OSDF can be defined as:

$$
\begin{aligned}
-lny_{1i} = \beta_0 &+ \sum_{m=2}^{M} \beta_m ln\frac{y_{mi}}{y_{1i}} + \frac{1}{2}\sum_{m=2}^{M}\sum_{n=2}^{M} \beta_{mn} ln\frac{y_{mi}}{y_{1i}} ln\frac{y_{ni}}{y_{1i}} + \sum_{k=1}^{K} \beta_k lnx_{ki} \\
&+ \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} lnx_{ki} lnx_{li} + \sum_{k=1}^{K}\sum_{m=2}^{M} \beta_{km} lnx_{ki} ln\frac{y_{mi}}{y_{1i}} + \sum_{m=1}^{M} \beta_{tm} t ln\frac{y_{mi}}{y_{1i}} \\
&+ \sum_{k=1}^{K} \beta_{tk} t lnx_{ki} + \sum_{j}^{J} \theta_{hj} D_j + \sum_{h}^{H} \theta_h lnC_h + v_i + u_i
\end{aligned}
$$

$$(\mathbf{11})$$

where v_i, is assumed to be an independent and identically distributed normal random variable with 0 mean and constant variance, iid [N~$(0,\sigma_v^2)$]. v_i is intended to capture random events, and its variance, σ_v^2, is a measure of the importance of random shocks in determining variation in output. Conversely, the inefficiency term u_i is non-negative and it is assumed to follow a half-normal distribution. Differences across vessels in the u_i are intended to capture differences in skill or efficiency (Alvarez and Schmidt 2006). To facilitate the interpretation of the parameters, we set the left side of the equation to ln y_1 rather than -ln y_1 as suggested by Coelli and Perelman (1999).

Finally, D_{oi} can be estimated as follows (Jondrow et al. 1982):

$$TE_i = D_{oi} = E(\exp(-u_i)|v_i - u_i) = -\frac{\sigma_u \cdot \sigma_v}{\sigma} \cdot \left[\frac{f((v_i - u_i) \cdot \lambda/\sigma)}{1 - F((v_i - u_i) \cdot \lambda/\sigma)} - \frac{(v_i - u_i) \cdot \lambda}{\sigma}\right] \tag{12}$$

where: σ_u and σ_v are, respectively, the standard deviations for u and v, $\lambda = \sigma_u / \sigma_v$, $f(\cdot)$ represent the standard normal density and $F(\cdot)$ the standard normal cumulative density functions.

DATA AND EMPIRICAL MODEL

Detailed trip-level data on harvest composition, fishing gear and effort, crew size, and vessel characteristics for those vertical line vessels that landed at least one pound of red snapper annually between 2001 and 2012 (6 years pre and post-IFQ) were obtained from the National Marine Fisheries Service. The analysis was limited to the vertical line vessels because they were responsible for the majority of the landings and to control for harvesting capital heterogeneity. Following common practice in productivity analyses, we aggregated the trip-level data into annual vessel-level observations to control for the confounding effects of seasonal changes. The resultant database had 3,854 (annual vessel-level) observations.

The empirical model specified four outputs and three inputs. The four species (or species groups), included were red snapper (y_1), vermilion snapper (y_2), red grouper (y_3); and other species (y_4). y_1 was used to normalize the OSDF and impose linear homogeneity in outputs. The three inputs used were crew size (x_1), number of days fished (x_2) and vessel length (x_3) which was a proxy measure quasi-fixed fishing capital.

The model also accounted for resource abundance, regulatory constraints, climate and regional variability. We only included red snapper exploitable biomass estimates in the model because of the absence of biomass data for the other jointly caught species. To account for regulatory environment, we incorporated a red snapper fishing season length variable and license type dummy variable. Depending on the type of license held, vessels could either harvest 2,000 (Class 1 license) or 200 (Class 2 license) lbs. of red snapper per trip. If a vessel held a Class 2 license then license type dummy was set equal to one. Climate variability was controlled using the multivariate El Niño Southern Oscillation (ENSO) index (MEI). MEI is a composite index made up of a number of variables used to measure ENSO events, including sea surface temperature, surface air temperature, sea-level pressure, zonal (*i.e.*, east-west) surface wind, meridional (*i.e.*, north-south) surface wind and total amount of cloudiness. Positive MEI values correspond to warm phases or El Niño events and negative values correspond to cool phases or La Niña events (Wolter and Timlin 1998). We also accounted from regional productivity differences. The studied area was divided into seven regions: South Texas (A); Northern Texas (B); Louisiana (C); Alabama and Mississippi (D); the Northern Florida (E); West Central Florida (F); and Southwest Florida (G). Area G was defined as the base level.

Table 2 describes pre (2001-2006) and post-IFQ (2007-2011) catch composition and participation trends. As noted earlier in the discussion, post-IFQ the remnant fleet took fewer but longer trips and diversified their catch mix. Descriptive statistics of the variables used in the model are presented in Table 3.

RESULTS AND DISCUSSION

Production frontier

Parameter estimates of the TL OSDF model are reported in Table 4. As customarily done, all variables in the TL models were normalized by their GM. First-order parameters of both inputs and outputs are statistically significant and display the expected signs which are consistent with economic theory. The null hypothesis that technical inefficiency does not exist (H_o: $\lambda = 0$) is rejected at the 1% level indicating that the stochastic production frontier specification is preferable to the conventional production function specification. In addition, the standard errors for u and v are statistically significant indicating that skill and random shocks are important in the description of the underlying technology.

Because the empirical model allows for the estimation of a non-constant and non-neutral production frontier, we estimated output and input distance elasticities and returns to scale (RTS) for the entire sample (12 years) and pre- and post-IFQ periods (Table 5). At the sample mean, partial input distance elasticities were equal to 0.44 and 1.05 for crew size and fishing days, respectively. The elasticity for quasi-fixed fishing capital component is 0.56 showing a positive relationship between vessel size and landings. All partial input elasticities were found to be statistically different from zero. Table 5 also shows the presence of increasing returns to scale suggesting the presence of overcapacity. Although, the magnitude of the RTS decreased after the IFQ program, overcapacity levels remain elevated indicating that the fleet has yet to achieve an economically optimal configuration.

Partial output distance elasticities are also reported in Table 5. In general terms, output distance elasticities capture the share of each species (or species' group) relative to the aggregate landings. Table 5 shows a statistically significant change in the output mix after the implementation of the IFQ. From a managerial point of view these changes are important because fishers' ability to control their catch composition means that improved management in one fishery may require improved management of those other lightly or under-regulated substitute species (Solís et al. 2014b).

The empirical model also controls for red snapper abundance, red snapper endorsements (Class 1 and 2), climate variability and season length. The coefficient for stock abundance is, as expected, positive and statistically significant, suggesting that an increase in fish stock induces an upward shift of the production possibility frontier. This result agrees with previous research underscoring the importance of accounting for stock abundance (Squires 1992; Jin et al. 2002; Felthoven et al. 2009; among others). The coefficient for Class 2 is negative and statistically significant indicating that those vessels with Class 2 licenses (200 lbs trip limits) were less productive than their counterparts. Climate variability was not found to be statistically significant.[5] This result may be explained by two main reasons. First, red snapper inhabits waters

[5] In preliminary analysis we tested three additional climatic indicators: 1) the annual and seasonal average sea surface temperature (SST); 2) the Japan Meteorological Agency (JMA) ENSO index; and, 3) the accumulated cyclone energy (ACE). As for the MEI index, none of these variables resulted to be statistically significant; and furthermore, including these variables affected the convergence of our ML function.

from 30–200 ft. deep, which tend to have stable temperature conditions. Moreover, Karnauskas et al. (2013) shows that sea surface temperatures have been fairly stable since the mid-1990's. In addition, the temporal (i.e., annual) aggregation of the data may affect the significance of the climate variable since fishers can forgo fishing during periods of rough seas and make up for their lost production later in the year when weather conditions are more favorable.

Finally, the open fishing season variable was found to be positive and statistically significant. That is, adding the flexibility to fish year-round offers significant productivity gains to the fishery. Specifically, the partial elasticity for open season is equal to 0.09. Thus, holding everything else constant, opening the harvesting season from pre-IFQ levels to its post-IFQ levels could increase aggregate harvest by a potential 23%.

Changes in TFP and its components

Table 6 presents TFP changes over the studied period. The reported estimates represent the change in MI between two consecutive years. Ratios greater than unity indicate an improvement in productivity, meaning that more harvest was produced with the same amount of inputs. Also, because annual estimates were calculated as GMs, the annual average rate of change in TFP for each year can be calculated by subtracting one from the estimate.

Between 2001 and 2012, the annual MIs ranged between 0.839 in the period 2006-2007 to 1.181 in the period 2009-2010. After the adoption of the IFQ program, productivity declined by 8.1 % in the period 2007-2008, which coincided with substantial reductions in the red snapper quota. The red snapper quota fell from 4.19 mp g.w. in 2006 to 2.99 mp g.w. (about 30% drop) in 2007 and then dropped again to 2.30 mp g.w. in 2008 (another 23%). To offset the impact of the reduced quota, fishers prolonged their fishing trips and diversified their landings (Agar et al. 2014). Table 2 shows that post-IFQ fishers directed their effort to other species, particularly vermilion snapper. In the period 2008-2009, productivity gains were first observed since the onset of the IFQ program. In this period, productivity increased by 5.8%, and then increased again by 18.1% in 2009-2010 and then by 8.8% in 2010-2011. In the period 2011-2012, productivity fell marginally by 4.2%. These productivity gains may have benefited from increases in the red snapper quota (Table 2).

Table 6 shows that the sexennial pre and post-IFQ geometric MI means were 0.930 and 1.041, respectively indicating that prior to the IFQ program the productivity of the red snapper fleet was declining at an annual rate of 7%, whereas after began increasing at an annual rate of 4.1%. Figure 4 shows that the kernel distribution of MI scores narrowed and median values increased post-IFQ.

Table 6 also reports TFP changes for the entire fleet and fleet categories: remnant fleet, retired fleet and (post-IFQ) newcomer or new entrant fleet. It shows that in the pre-IFQ period both the remnant and retired fleets experienced declining productivity; however, the fleet that left the fishery experienced higher productivity declines (12.5% vs. 4%). Post-IFQ the productivity of the remnant fleet rose from -4% to 2.7%. Table 6 also reports that newcomer fleet was extremely productive reporting annual productivity gains in the order of 21.2%. Geographically, productivity gains were more pronounced in Louisiana and northern Texas relative to central and south Florida because derby fishing conditions were common in the western Gulf (Agar et al. 2014). Eastern Gulf catches only recently grew owing to the eastward expansion of the red snapper stock along the West Florida shelf (Table 7).

With respect to the sources of TFP change, Table 8 shows that post-IFQ productivity gains benefitted the most from changes in technical efficiency rather than from technological progress or changes in stock size. Sexennial pre- and post-IFQ average show that EC rose from -6.3% to 3.4% whereas TC increased from -0.8 to 0.2% and SC rose by 0.5% during the same time period. In the Post-IFQ period, EC was the main source of productivity growth accounting for 83% of the TFP changes while SC and TC accounted for 12% and 5% of the observed gains, respectively (Table 8). Finally, Figure 5 shows that in the pre-IFQ period, vessels in the retired fleet had, on average, lower TE levels, which was one of the anticipated effects of IFQ programs. Most of the vessels that left the fishery held Class 2 licenses (200 lbs. of red snapper trip limits).

CONCLUSIONS

This paper investigated the impact of the GOM red snapper IFQ program on the productivity of the vertical line commercial fleet. The findings of the study suggest that the IFQ program had a positive impact on the productivity of the fleet. Sexennial pre and post-IFQ MIs show that productivity gains rose from -7% to 4.1%.

The study also identified the main drivers of productivity growth. It found that most of the post-IFQ productivity gains were driven by changes in technical efficiency (83%) followed by changes in stock abundance (12%) and technical change (5%). Technical efficiency improved the most because the added flexibility afforded by the program which influenced both extensive and intensive margins. Changes in the extensive margins came about by the release of redundant capital and labor whereas changes in the intensive margin came about easing of regulatory constraints such as trip limits and fishing seasons.

In light of these results and earlier work suggesting that the current fleet is over-dimensioned, regulators interested in spurring productivity gains may want consider short-run policies that remove surplus capital and labor rather than those that provide research and development opportunities. Once the harvesting capacity becomes more closely aligned with the reproductive potential of the stock then regulators may want to revisit policies that support research and development. However, productivity gains from common-pool resources cannot be sustained indefinitely because harvest quotas are set based on conservative exploitation levels to protect the finite reproductive potential of the stock.

Last, we observe that the method used in this study is based on the comparison of vessel-level productivity levels between two consecutive years. Since an unbalanced data set was used in this study, some of the observations were eliminated from the analysis. To check on any potential biased, we re-estimated our model measuring the MI as the change in year t productivity level and the next available productivity level for that vessel. This alternative approach gave us similar outcomes to the one presented above with less than 2% discrepancy among the estimates. However, this is an area that deserves further research.

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Table 1. Recent Empirical Studies Measuring Changes in Productivity in Fishing

First Author (Year of Pub.)	Fishery (Country/ies)	Method*	Multi-outputs	Control Variables‡	Quotas	Metrics†	Period of Analysis
Eggert (2013)	Mixed Species (Iceland, Norway, Sweden)	PI	No	S	No	TFP	1973-2003
Felthoven (2009)	Pollock (USA)	St	Yes	S, C, R	Yes	PC	1994–2003
Fox (2003)	Halibut (Canada)	PI	No	S	Yes	PC, PR	1988, 1991,1994
Fox (2006)	Mixed Species (Australia)	PI	No	S	Yes	PC, PR	1997-2000
Greeneville (2006)	Mixed Species (Norway)	St	No	--	No	TE, TFP	1997-2003
Hannesson (2007)	Mixed Species (Norway)	PI	No	S	No	TFP	1961–2004
Hannesson (2010)	Mixed Species (Norway)	PI	No	S	No	TC, TFP	186-1983
Hoff (2006)	Mixed Species (Denmark)	DEA	Yes	--	No	TE, SE, TC, TFP	1987–1999
Islam (2011)	Mixed Species (Malaysia)	PI	No	--	No	TFP	1990-2005
Jin (2002)	Groundfish (USA)	PI	Yes	S, R	No	TFP	1964-1993
Kim (2012)	Mixed Species (Korea)	DEA	Yes	S	No	TE, SE, TC, TFP	1995-2009
O'Donnell (2013)	Mixed Species (Australia)	St	Yes	C	No	TE, SE, TFP, EC	1974-2010
Oliveira (2009)	Mixed Species (Portugal)	DEA	Yes	S	Yes	TE, TC, TFP	1995-2004
Squires (1992)	Mixed Species (USA)	PI	Yes	S, R	Yes	TFP	1981-1989

Squires (2008)	Tuna (Korea)	DEA	Yes	S, C	No	TE, TC, TFP	1997-2000
Stephan (2013)	Multiple fisheries (Australia)	PI	Yes	S	Yes	TFP	1993-2012
Walden (2012)	Quahogs & Clams (USA)	DEA	Yes	S	Yes	TE, SE, TC, TFP	1980–2008
Walden (2013)	Groundfish (USA)	PI	Yes	-	Yes	TFP/EHI	1996-2010
Walden (2014)	Groundfish (USA)	PI	Yes	S	Yes	TFP/EHI	2007-2011

*: Stochastic (**St**), Data Envelopment Analysis (**DEA**); Productivity Index (**PI**)
‡: Stock (**S**); Climate (**C**); Regulations (**R**); Quotas (**Q**)
†: Technical Efficiency (**TE**); Scale Efficiency (**SE**); Technological Change (**TC**), Productivity Change (**PC**); Total Factor Productivity (**TFP**); Profit ratio (**PR**); Environmental Change (**EC**); EHI Economic health index (**EHI**)

Table 2. Evolution of Key Characteristics of the Red Snapper Fleet

Year	Average			Landings (1,000's lbs)				No. of Vessels	Season Length (days)	Annual Quota (mp g.w)
	No. of Trips	Days at Sea	Crew size per trip	Red Snapper	Vermilion Snapper	Red Grouper	Other			
2001	7,538	58.52	2.63	3,399	1,368	952	3,3401	357	79	4.189
2002	7,972	58.44	2.62	3,588	1,653	916	3,5317	371	91	4.189
2003	7,918	60.60	2.66	3,839	1,999	679	3,279	377	94	4.189
2004	7,663	55.54	2.62	3,532	1,768	828	3,485	400	105	4.189
2005	6,484	48.99	2.53	2,962	1,448	916	2,876	391	131	4.189
2006	6,225	56.82	2.55	3,696	1,406	881	2,238	356	126	4.189
2007	3,822	61.07	2.63	2,413	1,759	830	1,923	261	365	2.986
2008	3,771	60.00	2.65	1,981	2,132	1,018	2,151	255	366	2.297
2009	3,933	64.40	2.67	2,038	2,438	1,025	1,960	240	365	2.297
2010	3,093	48.25	2.61	2,565	1,522	918	1,615	294	365	3.191
2011	3,347	56.19	2.69	2,720	2,281	1,382	1,914	292	365	3.300
2012	3,288	63.34	2.72	3,185	1,774	1,822	2,077	284	366	3.712

Table 3. Descriptive Statistics of the Harvesting Activities

Variable (units)	Whole Sample		Pre IFQ		Post IFQ		Test of means[a]
	Mean	SD	Mean	SD	Mean	SD	
y_1 (lbs/trip)	548	1049	500	755	648	1476	0.00
y_2 (lbs/trip)	330	841	230	678	535	1075	0.00
y_3 (lbs/trip)	174	414	121	317	284	546	0.00
y_4 (lbs/trip)	480	914	461	884	520	972	0.00
x_1 (crew/trip)	2.74	1.17	2.78	1.22	2.66	1.06	0.00
x_2 (days/trip)	3.34	2.59	2.96	2.35	4.12	2.87	0.00
x_3 (feet)	38.50	10.09	38.90	10.60	37.70	8.91	0.00
Area A (dummy)	0.02	--	0.03	--	0.01	--	0.00
Area B (dummy)	0.10	--	0.12	--	0.06	--	0.00
Area C (dummy)	0.12	--	0.14	--	0.06	--	0.00
Area D (dummy)	0.26	--	0.27	--	0.25	--	0.00
Area E (dummy)	0.32	--	0.28	--	0.40	--	0.00
Area F (dummy)	0.16	--	0.14	--	0.21	--	0.00
Area G (dummy)	0.02	--	0.02	--	0.02	--	0.77
Class 2 (dummy)	0.59	--	0.58	--	0.61	--	0.00
Log RS stock	11.07	0.79	10.74	0.76	11.54	0.56	0.00
Open season (days)	213.06	129.34	104.55	18.62	365.33	0.47	0.00

[a] Test (P-values) before and after the implementation of the IFQs.

Table 4. Parameter Estimates of the OSDF Model

Parameter[a]	**Coefficient**	**SE**
Constant	9.365***	(0.308)
Y_2	-0.067***	(0.007)
Y_3	-0.157***	(0.008)
Y_4	-0.357***	(0.012)
$Y_2 * Y_2$	-0.012***	(0.002)
$Y_3 * Y_3$	-0.031***	(0.002)
$Y_4 * Y_4$	-0.079***	(0.003)
$Y_2 * Y_3$	0.005***	(0.001)
$Y_2 * Y_4$	-0.002	(0.002)
$Y_3 * Y_4$	0.014***	(0.002)
x_1	0.432***	(0.065)
x_2	1.074***	(0.022)
x_3	0.210**	(0.096)
$x_1 * x_1$	-0.468***	(0.125)
$x_2 * x_2$	-0.034**	(0.014)
$x_3 * x_3$	-0.259	(0.251)
$x_1 * x_2$	0.064**	(0.027)
$x_1 * x_3$	-0.073	(0.146)
$x_2 * x_3$	-0.070*	(0.041)
$Y_2 * x_1$	0.020**	(0.009)
$Y_2 * x_2$	-0.004	(0.003)
$Y_2 * x_3$	-0.031**	(0.015)
$Y_3 * x_1$	0.011	(0.008)
$Y_3 * x_2$	-0.014***	(0.003)
$Y_3 * x_3$	-0.004	(0.012)
$Y_4 * x_1$	-0.013	(0.013)
$Y_4 * x_2$	-0.005	(0.005)
$Y_4 * x_3$	-0.028	(0.021)
$Y_2 * t$	-0.231**	(0.107)
$Y_3 * t$	0.008	(0.096)
$Y_4 * t$	0.188**	(0.094)
$x_1 * t$	-0.002	(0.075)
$x_2 * t$	0.533***	(0.068)
$x_3 * t$	0.284***	(0.068)
Area A	-0.002**	(0.001)
Area B	-0.005***	(0.001)
Area C	-0.007***	(0.002)
Area D	0.001	(0.009)
Area E	-0.003	(0.003)
Area F	0.059***	(0.014)
Stock	0.064**	(0.032)

Open season	0.091***	(0.014)
Class 2	-0.690***	(0.041)
MEI	0.014	(0.027)
σ_u	0.780***	
σ_v	0.391***	
$\lambda = \sigma_u / \sigma_v$	1.99**	
Log-Likelihood	3,504	
N	3,855	

*P < 0.10; **P < 0.05; ***P < 0.01

[a] To impose linear homogeneity in outputs the right hand side outputs are normalized by red snapper *e.g.*, $Y_2 = y_2/y_1$.

Table 5. Partial Distance Input and Output Elasticities and Returns To Scale (RTS)

Elasticities	**Whole Sample**	**Pre IFQ**	**Post IFQ**
y_1	-0.42***	-0.43***	-0.39***
y_2	-0.07***	-0.05***	-0.10***
y_3	-0.16***	-0.13***	-0.18***
y_4	-0.36***	-0.39***	-0.33***
x_1	0.44***	0.43***	0.44***
x_2	1.05***	1.07***	1.03***
x_3	0.56**	0.72**	0.42**
RTS	2.05	2.22	1.89

*$P < 0.10$; **$P < 0.05$; ***$P < 0.01$

Table 6. Evolution of TFP Scores for the Entire Sample and Fleet Categories

Period	All vessels	Remnant	Retired	Newcomer
2001-2002	0.954	0.994	0.908	--
2002-2003	0.894	0.945	0.824	--
2003-2004	0.971	0.949	1.010	--
2004-2005	0.850	0.881	0.781	--
2005-2006	0.990	1.032	0.818	--
2006-2007	0.839	0.839	--	--
2007-2008	0.919	0.966	--	0.853
2008-2009	1.058	1.012	--	1.617
2009-2010	1.181	1.138	--	1.325
2010-2011	1.088	1.065	--	1.214
2011-2012	0.958	0.953	--	1.05
Pre-IFQ*	0.930	0.960	0.875	--
Post-IFQ*	1.041	1.027	--	1.212

* weighted average (by number of vessels)

Table 7. Average TE Levels Pre and Post-IFQs by Geographic Areas

Period	Areas						
	STX	NTX	LA	MS&AL	NFL	CFL	SFL
Pre-IFQ	0.574	0.562	0.550	0.561	0.587	0.595	0.578
Post-IFQ	0.555	0.598	0.618	0.573	0.570	0.524	0.478
Rate of Change	-3.3	6.4	12.36	2.2	-2.9	-11.9	-17.3

Table 8. Geometric Means of MI and its Components

Period	TFP	EC	TC	SC
2001-2002	0.954	0.953	1.002	1.000
2002-2003	0.894	0.893	1.001	1.000
2003-2004	0.971	0.970	1.001	1.000
2004-2005	0.850	0.863	0.983	0.998
2005-2006	0.990	0.991	0.999	0.999
2006-2007	0.839	0.887	0.946	1.003
2007-2008	0.919	0.921	0.997	1.001
2008-2009	1.058	1.056	0.999	1.003
2009-2010	1.181	1.178	1.000	1.003
2010-2011	1.088	1.080	1.005	1.003
2011-2012	0.958	0.950	1.002	1.005
Pre-IFQ*	0.930	0.937	0.992	1.000
Post-IFQ*	1.041	1.034	1.002	1.005

* weighted average (by number of vessels)

Figure 1. Landings and Revenue Profiles of the US Gulf of Mexico Red Snapper Fishery

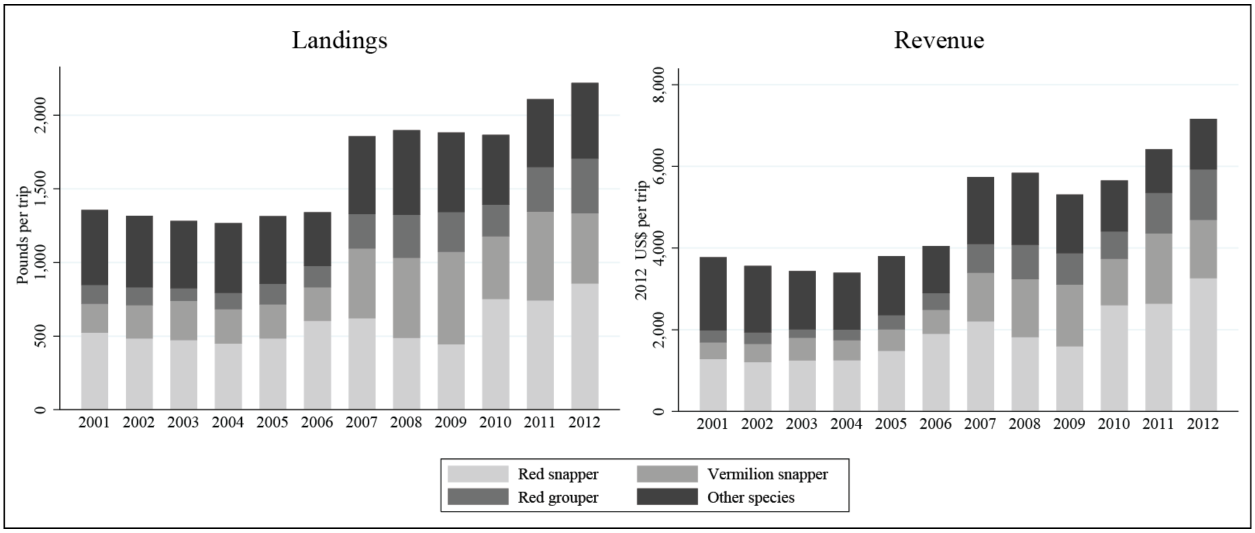

Figure 2. Fixed Base Indices for Number of Vessels, Vessel Length, Days at Sea and Crew Days

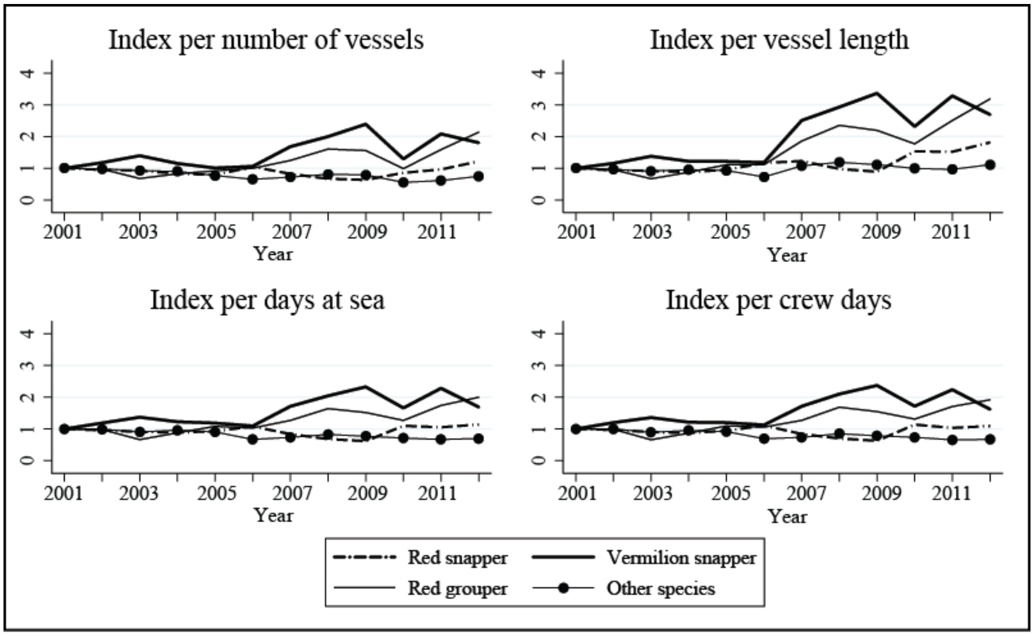

Figure 3. Illustration of the Decomposition of MI.

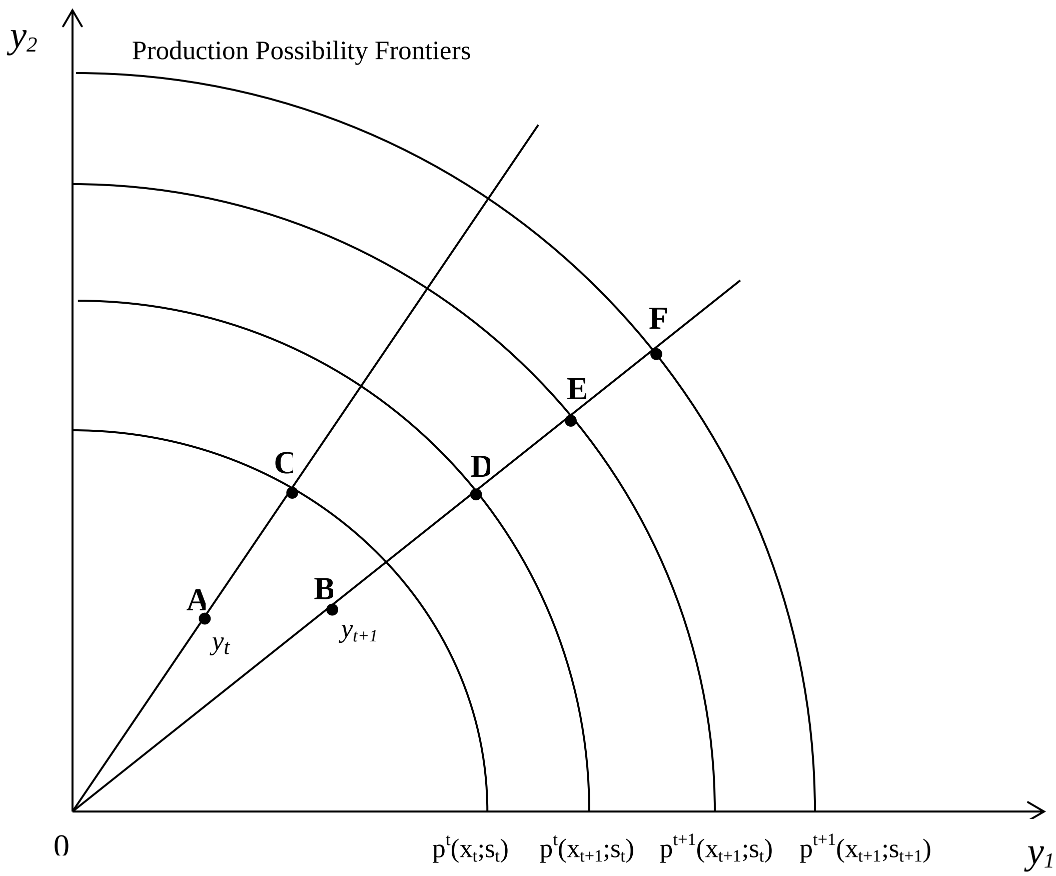

Figure 4. Pre and Post-IFQ MI Kernel Distributions

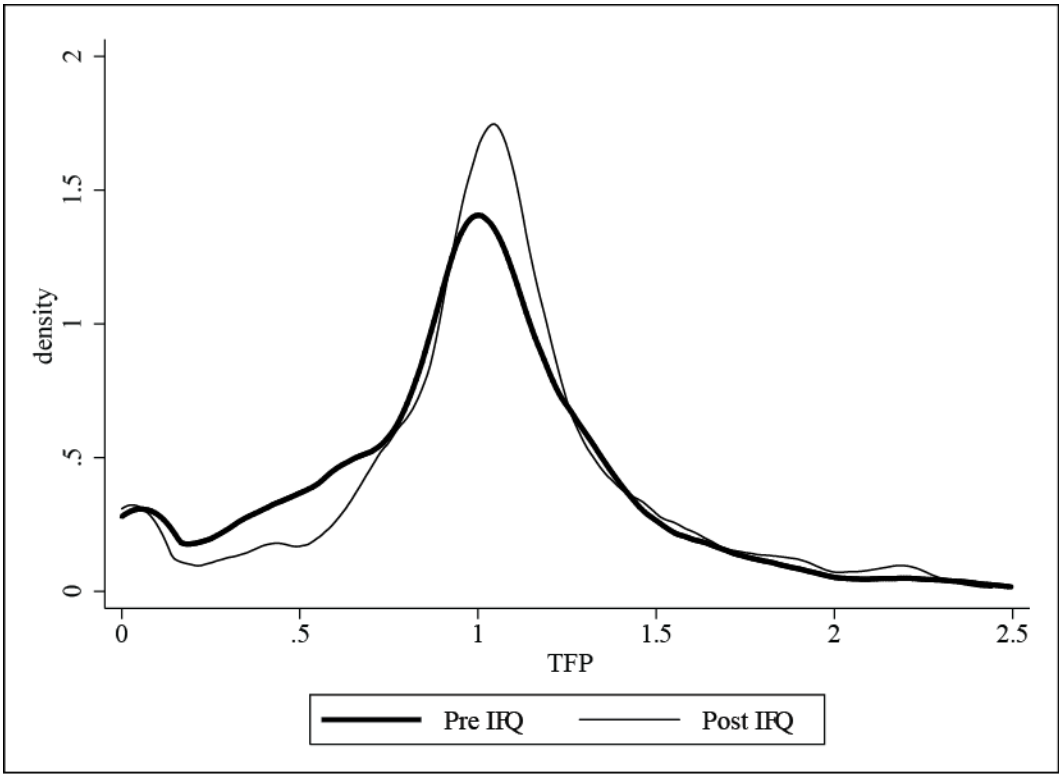

Figure 5. Distribution of Pre-IFQ TE Scores for the Retired and Remnant Fleets (2001-06)