Marine Policy 62 (2015) 347–357

Contents lists available at ScienceDirect

Marine Policy

journal homepage: www.elsevier.com/locate/marpol

IFQs and total factor productivity changes: The case of the Gulf of Mexico red snapper fishery

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A R T I C L E I N F O

Article history:
Received 20 April 2015
Received in revised form
1 June 2015
Accepted 1 June 2015
Available online 19 June 2015

Keywords:
Productivity change
Individual fishing quotas
stochastic frontier distance function

A B S T R A C T

This study 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 Malmquist indices were derived from an output-oriented stochastic distance frontier. The analysis 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.

1. Introduction

Capture fisheries around the world are increasingly being managed with individual fishing quotas (IFQs). Today, about one-quarter of the global marine harvest is managed with IFQs [1]. Under an IFQ program, fishers are assigned exclusive harvesting privileges based on a share of the quota, which is expected to balance the harvesting capacity of the fleet with the productivity of fish stocks. Fishers are not only anticipated 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 quotas (or 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 [2,3]. Costello et al. [4] concluded that the adoption of IFQs reduced the likelihood of stock collapse, whereas [5] reported that IFQs have contributed to higher catches. However, this latter claim has been challenged by [6], who argued that some of the observed catch gains may be due to improved catch reporting systems often concurrently put in place with IFQs. The extant economic literature has generally viewed IFQs favorably, highlighting that a sounder 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 [7–12]. 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 quota shares [13,14,11]. In contrast, most of the literature dealing with the social impacts of IFQs has been critical focusing on fairness and equity concerns [9,15,16]. This literature described how the distribution and concentration of quota resulted in fewer at sea and on-land employment opportunities, disadvantaged small fishing communities, lowered wages and bargaining power of crew and captains, generated class divisions, and created 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 more fish with the same amount of inputs or harvest the same amount of fish using fewer inputs [17]. 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

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http://dx.doi.org/10.1016/j.marpol.2015.06.001

achieved by reducing redundant capital and labor by transferring of quota from less to more efficient vessels [17].

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. The study also decomposes the sources of TFP growth into technological progress, changes in technical efficiency and stock change using a Malmquist Index (MI) derived from an output-oriented stochastic distance frontier (OSDF). The use 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 [18–20, among others]. The red snapper fishery was selected as a case study because it is one the most valuable commercial fisheries in the GOM.

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, the data and methods are described and the empirical model introduced. Then, the results are presented and discussed. The article concludes with a summary of the main findings and policy implications.

2. 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 in 1984 which established minimum size fish 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 [21,22].

In the 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, impose tiered trips limits (200 and 2000 lb), and establish a red snapper endorsement system. In 1995, a new stock assessment indicated 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 [21]. Unfortunately, the larger quota and tiered trip limits and fishing seasons failed to slow down the fishery [23].

To address the adverse socio-economic impacts of progressively shorter fishing seasons, the Council limited fishing to the first 15 days of each month (reduced to only 10 days later on) or until the quota was reached. The Council also established a permanent, two tiered red snapper license system made up of Class 1 and Class 2 licenses, which allowed fishers to harvest 2000 and 200 lb trip limit, respectively. Table 1 offers a summary of the main regulations [24].

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

Since adoption of the IFQ program, significant structural changes have taken place. Agar et al. [24], who reviewed the performance of the first five years of the IFQ program, found 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, [20] 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 also were documented [25]. Share and lease prices increased significantly suggesting that the profitability of the fishery improved. In addition, there were no quota overages since the IFQ program began. However, the stock remains overfished, although it is not undergoing overfishing [24]. The review also found that the IFQ program was successful in mitigating the race to fish behavior. The fishing season expanded from a 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 [24]. Fishers also began taking longer fishing trips and diversifying the composition of their output mix by targeting more vermilion snapper and red grouper (Fig. 1). Cursory review of single factor productivity indices (Fig. 2) shows important productivity gains in the harvest of vermilion snapper and red grouper and minor gains in the harvest of red snapper following adoption of the IFQ program. However, these partial metrics fail to account for potentially confounding effects such as changes in resource and market conditions, which may offer a distorted view of the productivity gains observed. The present study sheds light on this key issue by rigorously measuring productivity changes before and after the adoption of the IFQ program.

3. Literature review

Productivity is a key economic indicator used to analyze the performance of production units [26]. In a fisheries setting, productivity captures the relationship between the quantity of fish produced (harvested) and the amount of inputs used. Fishing fleets become more productive when they catch the same amount of fish with fewer inputs. Because of the multispecies and stochastic nature of the harvesting process different approaches have been employed to measure TFP growth in commercial fisheries. Table 2 presents a summary of recent empirical studies in this area of research.

The most straightforward approach is to construct productivity indexes using index numbers, such as Laspeyres, Lowe, Fisher, Paasche, and Törnqvist indexes. Productivity indexes have become very popular in the literature because they are easy to calculate and require less data when compare to other approaches [27].

Squires [28] was the first to extended the standard TFP index 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 [28,29] estimated changes in TFP in the New England groundfish fishery. Both, [28,29], 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 [30] used a stock corrected Fisher index to study productivity trends for key Commonwealth fisheries in Australia. These authors found an increasing trend in productivity especially after the introduction of a buyback program. Also using index numbers [31,32] decomposed profit and productivity in the British Columbia halibut fishery. Fox et al. [31] found that individual harvesting rights had a positive effect on industry performance mainly because an increase in output prices. Walden [33,34] found that the economic well-being of the northeast U.S. multispecies trawl fleet increased after the

Table 1
Regulatory History of the Commercial Gulf of Mexico Red Snapper Fishery.

Year	Season length (days)	Quota[a] (mp gw)	Harvest (mp gw)	Size limit (in)	Management actions
1984	365	NA	NA	13	Reef Fish Fishery Management Plan: Minimum size
1990	365	2.79	2.40	13	Amendment 1: established commercial quota, bottom longlines prohibited within 50 fathoms west of Cape San Blas, FL and within 20 fathoms elsewhere
1991	236	1.84	2.02	13	Regulatory Amendment: reduced TAC by 20%
1992	95	1.84	2.81	13	Emergency rule: April 3–May 14 1000 lb trip limit. Amendment 4: moratorium on new reef fish permits, emergency rules: 2000 lb endorsement or 200 lb trip limit, closed fishery December 1
1993	94	2.76	3.08	13	Regulatory Amendment: Opened February 10, one trip per day limit. Amendment 6: extended endorsements
1994	77	2.76	2.93	14	Regulatory Amendment: Opened February 24. Amendment 5: raised minimum size over next 5 years, establish Class 1 and Class 2 licenses. Amendment 9: extended reef fish permit moratorium
1995	52	2.76	2.65	15	Regulatory Amendment: opened February 28
1996	87	4.19	3.90	15	Regulatory amendment: Increase TAC, split quota into spring and fall seasons. Amendment 13: extended endorsement
1997	73	4.19	4.34	15	Regulatory amendment: fall season started Sept 2 for 1st 15 days/month until quota met
1998	72	4.19	4.22	15	Regulatory amendment: fall season started Sept 1, 1st 10 days/month. Amendment 15: established permanent red snapper Class 1 and Class 2 license, allocated ⅔ quota to spring, starts Feb 1,
1999	70	4.19	4.40	15	Interim rule: spring season reduced from 15 to 10 days/month
2000	66	4.19	4.36	15	Regulatory amendment: spring season open on February 1 for 10 days each month until spring-quota reached (2/3 commercial quota), Fall season open October 1 for 10 days each month until remaining quota reached. Amendment 17: extended permit moratorium for 5 more years
2001	79	4.19	4.18	15	None
2002	91	4.19	4.32	15	None
2003	94	4.19	3.99	15	None
2004	105	4.19	4.21	15	None
2005	131	4.19	3.69	15	Amendment 24: extended reef fish permit moratorium indefinitely
2006	126	4.19	4.21	15	None
2007	365	2.99	2.87	13	Amendment 26: implemented commercial red snapper IFQ program, reduced quota from 2006 level, mid-year quota increase, reduced size limit
2008	366	2.30	2.24	13	Reduced quota from 2007 level
2009	365	2.30	2.24	13	None
2010	365	3.19	3.06	13	Mid-year quota increase. Area closed due to oil spill
2011	365	3.30	3.24	13	Mid-year quota increase
2012	366	3.71	3.64	13	Mid-year quota increase

Source: Adapted from Table 1 in [24].

[a] Million pounds gutted weight (mp gw).

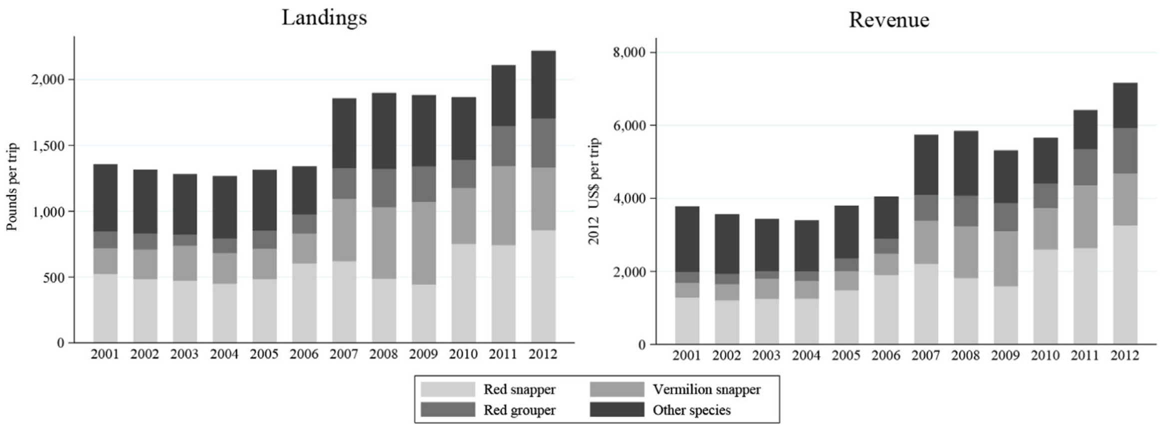

Fig. 1. Landings and revenue profiles of the US Gulf of Mexico red snapper fishery.

implementation of catch shares. Other productivity studies using productivity indexes include [35], who studied fisheries off the coast of Peninsular Malaysia, [36], who compared the Icelandic, Norwegian and Swedish fisheries, and [37,38], who assessed the Lofoten fishery in Norway. One of the main drawbacks of the productivity index approach is that by aggregating inputs and outputs, technological interdependencies cannot be assessed.

An alternative framework to measure TFP is to use 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

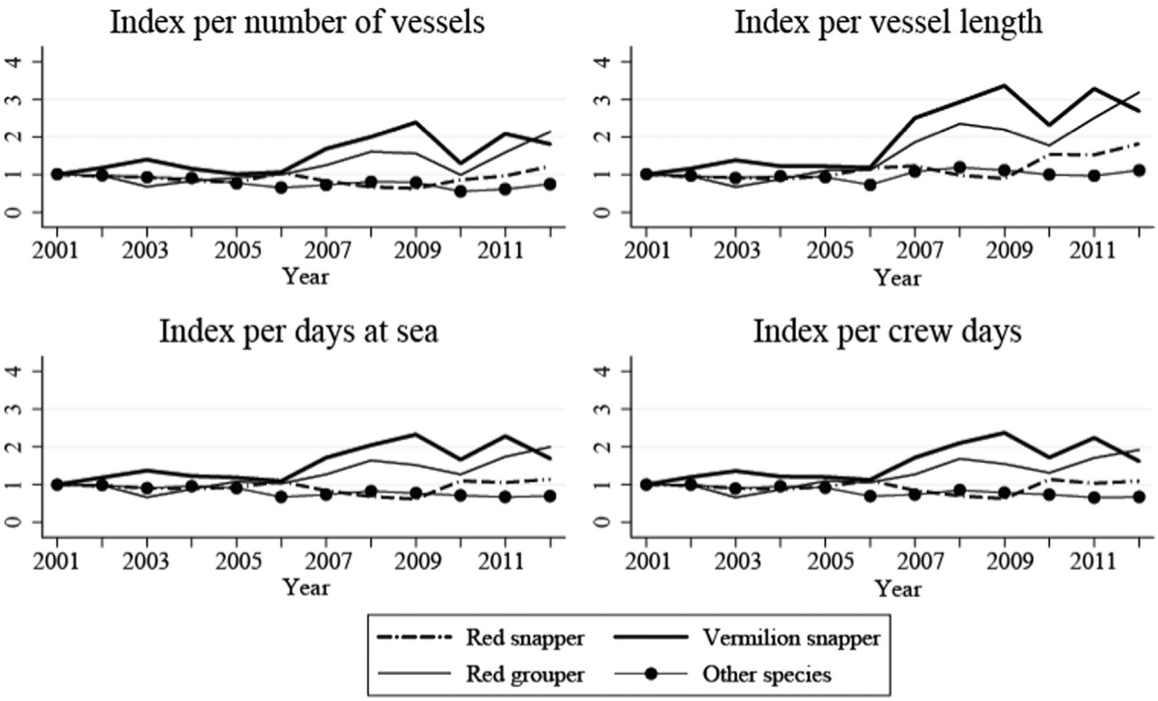

Fig. 2. Fixed base indices for number of vessels, vessel length, days at sea and crew days.

Table 2
Recent empirical studies measuring changes in productivity in fishing.

Reference	First author (year of pub.)	Fishery (country/ies)	Method[a]	Multi-outputs	Control variables[b]	Quotas	Metrics[c]	Period of analysis
[36]	Eggert (2013)	Mixed Species (Iceland, Norway, Sweden)	PI	No	S	No	TFP	1973–2003
[19]	Felthoven (2009)	Pollock (USA)	St	Yes	S, C, R	Yes	PC	1994–2003
[31]	Fox (2003)	Halibut (Canada)	PI	No	S	Yes	PC, PR	1988, 1991, 1994
[32]	Fox (2006)	Mixed Species (Australia)	PI	No	S	Yes	PC, PR	1997–2000
[37]	Hannesson (2007)	Mixed Species (Norway)	PI	No	S	No	TFP	1961–2004
[38]	Hannesson (2010)	Mixed Species (Norway)	PI	No	S	No	TC, TFP	1860–1983
[40]	Hoff (2006)	Mixed Species (Denmark)	DEA	Yes	–	No	TE, SE, TC, TFP	1987–1999
[35]	Islam (2011)	Mixed Species (Malaysia)	PI	No	–	No	TFP	1990–2005
[29]	Jin (2002)	Groundfish (USA)	PI	Yes	S, R	No	TFP	1964–1993
[43]	Kim (2012)	Mixed Species (Korea)	DEA	Yes	S	No	TE, SE, TC, TFP	1995–2009
[45]	O'Donnell (2013)	Mixed Species (Australia)	St	Yes	C	No	TE, SE, TFP, EC	1974–2010
[42]	Oliveira (2009)	Mixed Species (Portugal)	DEA	Yes	S	Yes	TE, TC, TFP	1995–2004
[28]	Squires (1992)	Mixed Species (USA)	PI	Yes	S, R	Yes	TFP	1981–1989
[41]	Squires (2008)	Tuna (Korea)	DEA	Yes	S, C	No	TE, TC, TFP	1997–2000
[30]	Stephan (2013)	Multiple fisheries (Australia)	PI	Yes	S	Yes	TFP	1993–2012
[39]	Walden (2012)	Quahogs & Clams (USA)	DEA	Yes	S	Yes	TE, SE, TC, TFP	1980–2008
[33]	Walden (2013)	Groundfish (USA)	PI	Yes	–	Yes	TFP/EHI	1996–2010
[34]	Walden (2014)	Groundfish (USA)	PI	Yes	S	Yes	TFP/EHI	2007–2011

[a] Stochastic (**St**) Data Envelopment Analysis (**DEA**) Productivity Index (**PI**)

[b] Stock (**S**); Climate (**C**); Regulations (**R**); Quotas (**Q**).

[c] 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**).

techniques to estimate production, cost, revenue or distance functions [27].

Within 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. [39] indicates that MI is advantageous for the study of 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 value for one or more outputs and the MI can ensure that those outputs stay zero.

Recent TFP studies using DEA in fishing include [39–43]. Of relevance to this study is the paper by [39], who studied the impact of IFQ on the productivity of the Mid-Atlantic surf clam and ocean quahog fishery, reported productivity gains immediately following the adoption of the IFQ program. However, these productivity gains were not sustained over time. The authors surmised that their results were driven by spatial changes in biomass and regulatory access restrictions to productive fishing grounds.

Despite the popularity of the DEA method, [18,19] 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 [44]. Hence, recent studies have argued that the stochastic frontier method is better suited to study harvesting processes because it allows for the inclusion of 'noise' in the estimation of the model. In addition, the parametric nature of this method 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 stochastic frontiers to measure TFP in fisheries. Felthoven et al. [19] measured productivity changes for the Alaskan Pollock fishery before and after the introduction of an exclusive harvesting privileges program. Using a quadratic transformation function, [19] found an increase in productivity over time, which was explained by changes in regulatory conditions, as well as by changes in climatic conditions, bycatch levels and stock abundance. However, this study did not explicitly decompose the TFP growth into its components. O'Donell [45] 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 are 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, it estimates MI using a multi-output/multi-input stochastic distance frontier (SDF) model, which to the best of our knowledge, is the first study deriving MI from a SDF in a multispecies fishery setting.[1]

4. Methods

This study estimates and decomposes productivity changes in the GOM red snapper fishery from 2001 to 2012 (6 years pre- and post-IFQ program) using MI. MI is an index-based approach that relies on radial distance functions. The SDF framework is used to estimate the model.

4.1. Distance function, malmquist productivity index and the decomposition of TFP

Coelli [46] 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 functions can be derived using input or output orientations. Orea et al. [18] state that output-oriented models are preferable for analyses of harvesting processes because of the quasi-fixed nature of fishing capital. 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

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

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 $D_o(x,y) \le 1$, then (x,y) belongs to $P(x)$. Additionally, if $D_o(x,y)=1$, then y is located on the outer boundary of $P(x)$ [46,47].

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

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

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

To account for resource abundance a stock size variable is incorporated in the calculation of the MI. Hence, a stock corrected MI can be computed as

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

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 change the study further decomposes 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 measures efficiency changes (movement toward the frontier) and SC identifies shifts in the frontier due to changes in stock abundance.

To decompose TFP Eq. (3) is first multiplied and divided by $D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_{t+1}\right)$:

$$\begin{aligned}
MI_{oi}(T_t,\ S_t) &= \frac{D_o^t\left(x_i^{t+1}, y_i^{t+1}; S_t\right)}{D_o^t\left(x_i^{t}, y_i^{t}; S_t\right)} \cdot \frac{D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_{t+1}\right)}{D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_{t+1}\right)} \\
MI_{oi}(T_t,\ S_t) &= \frac{D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_{t+1}\right)}{D_o^t\left(x_i^{t}, y_i^{t}; S_t\right)} \cdot \frac{D_o^t\left(x_i^{t+1}, y_i^{t+1}; S_t\right)}{D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_{t+1}\right)} \\
&= EC \cdot \frac{D_o^t\left(x_i^{t+1}, y_i^{t+1}; S_t\right)}{D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_{t+1}\right)}
\end{aligned} \tag{4}$$

Then, Eq. (4) is multiplied and divided by $D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_t\right)$:

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[1] Previous studies measuring MI in fishing have used DEA (Table 2).

[2] Previous studies have only assessed the effect of stock abundance on production levels [28,29,19]. However, in this study the influence of stock abundance on the vessel's changes of productivity levels is explicitly accounted for by including stock abundance as an additional component of TFP. Due to data limitations only the effect of the target species (red snapper) is included in the empirical estimation and decomposition of the MI.

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

$$MI_{oi}(T_t,\ S_t) = EC\cdot\frac{D_o^t\left(x_i^{t+1}, y_i^{t+1}; S_t\right)}{D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_t\right)}\cdot\frac{D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_t\right)}{D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_{t+1}\right)} = EC\cdot TC\cdot SC \tag{5}$$

To assist with the interpretation of the MI and its decomposition, a graphical depiction of a deterministic, multiproduct (2-species) harvesting process is presented in Fig. 3.[3] MI is calculated by dividing $D_o^t\left(x_i^{t+1}, y_i^{t+1}; S_t\right)$ – represented by OB/OD in Fig. 3 – by $D_o^t\left(x_i^t, y_i^t; S_t\right)$ or OA/OC. This overall efficiency metric is measured assuming that 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 has become more productive.

Now, let us decompose the MI into its three components. EC allows comparisons of the efficiency of a vessel across time periods. Specifically, EC measures whether a vessel gets closer to (or further away from) the best-practice frontier. If the efficiency for a vessel in the period $t+1$ is greater than in the period t then EC is positive and the estimated ratio will be greater than one. EC is simply calculated by dividing $D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_{t+1}\right)$ by $D_o^t\left(x_i^t, y_i^t; S_t\right)$ or OB/OF and OA/OC in Fig. 3, respectively. TC measures how much the production possibility frontier shifts between two time periods and can be computed by dividing $D_o^t\left(x_i^{t+1}, y_i^{t+1}; S_t\right)$ or OB/OD in Fig. 3 and $D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_t\right)$. Alternatively, TC equals OB/OE:

$$TC = \frac{OB}{OD}/\frac{OB}{OE} = \frac{OE}{OD} \tag{6}$$

In other words, if the production possibility set moves upwards then TC 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 $D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_t\right)$ or OB/OE by $D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_{t+1}\right)$ or OB/OF. Mathematically,

$$SC = \frac{OB}{OE}/\frac{OB}{OF} = \frac{OF}{OE} \tag{7}$$

Because the brenchmark period (time period t or $t+1$) is set arbitrarily the MI has customarily been defined as the geometric mean (GM) of two time-periods [48]. In doing so, MI is estimated as MI_{oi} instead of $MI_{oi}(T_t)$. The main implication of this approach is that TC is also calculated as a GM.[4] Since the analysis also includes SC, this component needs to be estimated as a GM as well. Consequently, MI_{oi} is estimated instead of $MI_{oi}(T_t, S_t)$, which is in line with the conventional productivity literature [39,41, among others]. TC and SC are now calculated as

$$TC = \left[\frac{D_o^t\left(x_i^{t+1}, y_i^{t+1}; S_t\right)}{D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_t\right)}\cdot\frac{D_o^t\left(x_i^t, y_i^t; S_t\right)}{D_o^{t+1}\left(x_i^t, y_i^t; S_t\right)}\right]^{0.5} \tag{8}$$

$$SC = \left[\frac{D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_t\right)}{D_o^{t+1}\left(x_i^{t+1}, y_i^{t+1}; S_{t+1}\right)}\cdot\frac{D_o^t\left(x_i^t, y_i^t; S_t\right)}{D_o^t\left(x_i^t, y_i^t; S_{t+1}\right)}\right]^{0.5} \tag{9}$$

4.2. Stochastic distance frontier

A translog functional form was selected to model the ODF. Coelli and Perelman [49] show that the translog functional form is a good approximation to the true distance function and is sufficiently flexible for the imposition of desirable properties such as homogeneity and symmetry. A translog ODF model can be described as

$$\begin{aligned}\ln D_{oi} = {} & \beta_0 + \sum_{m=1}^{M}\beta_m \ln y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\beta_{mn}\ln y_{mi}\ln y_{ni} \\ & + \sum_{k=1}^{K}\beta_k \ln x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln x_{ki}\ln x_{li} \\ & + \sum_{k=1}^{K}\sum_{m=1}^{M}\beta_{km}\ln x_{ki}\ln y_{mi} + \sum_{m=1}^{M}\beta_{tm}t\ln y_{mi} \\ & + \sum_{k=1}^{K}\beta_{tk}t\ln x_{ki} + \sum_{j}^{J}\theta_j D_j + \sum_{h}^{H}\theta_h \ln C_h\end{aligned} \tag{10}$$

where D_{oi} denotes the output distance function measure, y_{mi} and x_{ki} are, respectively, the production level of output m and the quantity of input k used by vessel i, D_j is a vector of j dummy variables and C_h is a vector of h control variables. Interactions of the time trend with input and output quantities were introduced to account for non-constant rate changes and for non-neutral technical change.

To satisfy the necessary conditions for a well-behaved ODF, the function is normalized by an arbitrary output and symmetry is imposed by setting $\beta_{mn} = \beta_{nm}$ and $\beta_{kl} = \beta_{lk}$[49]. After imposing these restrictions, the study defines the distance from each observation to the frontier as inefficiency (*i.e.*, $\ln D_{oi} = -u_i$) and adds a random noise variable (v_i) into the model (Eq. (10)). The OSDF takes the following form:

$$\begin{aligned}-\ln y_{1i} = {} & \beta_0 + \sum_{m=2}^{M}\beta_m \ln\frac{y_{mi}}{y_{1i}} + \frac{1}{2}\sum_{m=2}^{M}\sum_{n=2}^{M}\beta_{mn}\ln\frac{y_{mi}}{y_{1i}}\ln\frac{y_{ni}}{y_{1i}} \\ & + \sum_{k=1}^{K}\beta_k \ln x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln x_{ki}\ln x_{li} \\ & + \sum_{k=1}^{K}\sum_{m=2}^{M}\beta_{km}\ln x_{ki}\ln\frac{y_{mi}}{y_{1i}} + \sum_{m=1}^{M}\beta_{tm}t\ln\frac{y_{mi}}{y_{1i}} \\ & + \sum_{k=1}^{K}\beta_{tk}t\ln x_{ki} + \sum_{j}^{J}\theta_{hj}D_j + \sum_{h}^{H}\theta_h \ln C_h + v_i + u_i\end{aligned} \tag{11}$$

where v_i, is assumed to be an independent and identically distributed normal random variable with 0 mean and constant variance, iid $[N\sim(0,\sigma_v^2)]$. 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 is assumed to follow a half-normal distribution. Differences across vessels in the $u_i$are intended to capture differences in skill or efficiency [50]. To facilitate the interpretation of the parameters, the left side of the equation is set to $\ln y_1$ rather than $-\ln y_1$ as suggested by [49]. Finally, TE scores are estimated following [51].

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

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

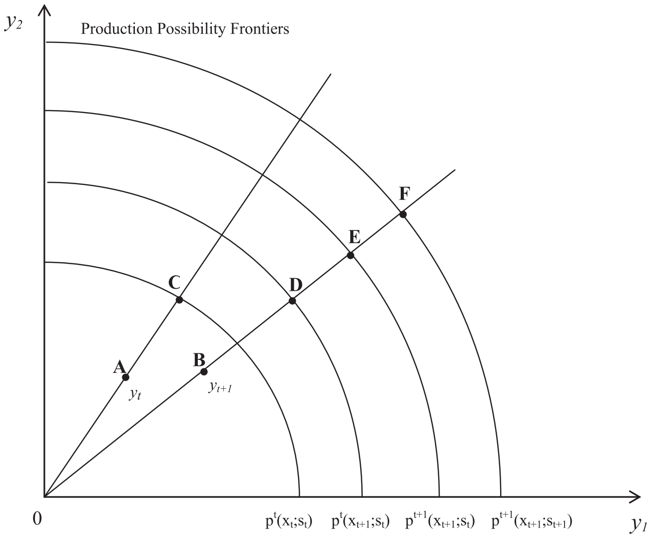

Fig. 3. Illustration of the decomposition of Malmquist Index (MI).
Note: p are the production possibility frontiers in time t as function of inputs (x) and stock (s).

Table 3
Evolution of key characteristics of the (sample).

Year	Average			Landings (1000's lb.)				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	7538	58.52	2.63	3399	1368	952	33401	357	79	4.189
2002	7972	58.44	2.62	3588	1653	916	35317	371	91	4.189
2003	7918	60.60	2.66	3839	1999	679	3279	377	94	4.189
2004	7663	55.54	2.62	3532	1768	828	3485	400	105	4.189
2005	6484	48.99	2.53	2962	1448	916	2876	391	131	4.189
2006	6225	56.82	2.55	3696	1406	881	2238	356	126	4.189
2007	3822	61.07	2.63	2413	1759	830	1923	261	365	2.986
2008	3771	60.00	2.65	1981	2132	1018	2151	255	366	2.297
2009	3933	64.40	2.67	2038	2438	1025	1960	240	365	2.297
2010	3093	48.25	2.61	2565	1522	918	1615	294	365	3.191
2011	3347	56.19	2.69	2720	2281	1382	1914	292	365	3.300
2012	3288	63.34	2.72	3185	1774	1822	2077	284	366	3.712

5. Data and empirical model

Detailed trip-level data on harvest composition, landing sites, fishing gear and effort, fishing grounds, crew size, and vessel characteristics for 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.[5] The GOM red snapper fishery was selected to examine changes in TFP because it was the first fishery in the GOM to transition from a command and control regime to an IFQ regime and continues to be an important source of income (Fig. 1). The analysis was limited to the vertical line fleet because is responsible for the majority of the red snapper landings and to control for harvesting capital heterogeneity. Following common practice in productivity analyses, the trip-level data were aggregated into annual vessel-level observations to control for the confounding effects of seasonal changes. The resultant database had 3854 (annual vessel-level) observations.

The empirical model specified four outputs and three inputs. The four species included were red snapper (y_1), vermilion snapper (y_2), red grouper (y_3), and other or miscellaneous species group (y_4). y_1 was used to normalize the OSDF and impose linear homogeneity in outputs. The three inputs used in the model were crew size (x_1), number of days fished (x_2) and vessel length (x_3), which was a proxy measure for quasi-fixed fishing capital. A similar input mix can be found in [18,19].

The model also accounted for resource abundance, regulatory constraints, climate and regional variability. Biomass estimates for red snapper (spawning biomass, eggs) were the only ones included in the model because of the absence recent estimates for the other jointly-caught species such as vermilion snapper and red grouper. To control for the regulatory environment, the model included variables to account for the length of the red snapper fishing season and the type of license held. Depending on the type of license held, vessels could either harvest 2000 (Class 1 license) or 200 (Class 2 license) lb of red snapper per trip. If a vessel held a Class 2 license then the 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 [52]. Regional productivity differences were also taken into account. 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 3 describes pre (2001-2006) and post-IFQ (2007–2011) catch composition and participation trends. As noted earlier in the discussion, the post-IFQ fleet took fewer but longer trips and diversified their catch mix. Descriptive statistics of the variables used in the model are presented in Table 4.

6. Results and discussion

6.1. Production frontier

Parameter estimates of the translog OSDF model are reported

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[5] Vessels participating in the GOM reef-fish commercial fishery are required to submit a record of each trip taken to the Logbook Program at the Southeast Fisheries Science Center in Miami, Florida. This mandatory, self-reported trip report contains information on dates of departure and offloading, harvest composition, landing sites, fishing gear and effort, fishing grounds and crew size. Information on vessel characteristics was collected through the federal permit application process by the Southeast Regional Office's Constituency Services Branch in St. Petersburg, Florida. Information about the Logbook Program and a copy of the trip report form are available at http://www.sefsc.noaa.gov/fisheries/reporting.htm.

Table 4
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 (eggs)[b]	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.

[b] Stock is measure as the natural logarithmic of spawning biomass, eggs.

in Table 5. As customarily done, all variables were normalized by their GM. First-order parameters of both inputs and outputs were statistically significant and showed the expected signs consistent with economic theory. The null hypothesis that technical inefficiency did not exist (H_o: $\lambda = 0$)was 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 were statistically significant at the 1% level 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, output and input distance elasticities and returns to scale (RTS) were estimated for the entire sample (12 years) and pre- and post-IFQ periods (Table 6). 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 was 0.56 showing a positive relationship between vessel size and landings. All partial input elasticities with the exception of vessel length were found to be statistically significant at the 1% level. The vessel length elasticity was found to be statistically significant at the 5% level. The findings reported in Table 6 also show increasing returns to scale (RTS) suggesting that the present fleet is larger than necessary to harvest the current TAC at the least cost. Asche et al. [53] note that high RTS are a sign of overcapacity, particularly in regulatory regimes that do not offer incentives to control capacity. Although, the RTS decreased slightly post-IFQ, the current fleet has yet to achieve an economically optimal configuration.

Table 6 reports the estimated partial output distance elasticities were all statistically significant at the 1% level. In general terms, output distance elasticities capture the share of each species (or species group) relative to aggregate landings. Table 6 shows a significant change in the output mix post-IFQ. From a

Table 5
Parameter estimates of the stochastic distance frontier 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)
$Y_2 \ast Y_2$	-0.012^{***}	(0.002)
$Y_3 \ast Y_3$	-0.031^{***}	(0.002)
$Y_4 \ast Y_4$	-0.079^{***}	(0.003)
$Y_2 \ast Y_3$	0.005^{***}	(0.001)
$Y_2 \ast Y_4$	-0.002	(0.002)
$Y_3 \ast Y_4$	0.014^{***}	(0.002)
x_1	0.432^{***}	(0.065)
x_2	1.074^{***}	(0.022)
x_3	0.210^{**}	(0.096)
$x_1 \ast x_1$	-0.468^{***}	(0.125)
$x_2 \ast x_2$	-0.034^{**}	(0.014)
$x_3 \ast x_3$	-0.259	(0.251)
$x_1 \ast x_2$	0.064^{**}	(0.027)
$x_1 \ast x_3$	-0.073	(0.146)
$x_2 \ast x_3$	-0.070^{*}	(0.041)
$Y_2 \ast x_1$	0.020^{**}	(0.009)
$Y_2 \ast x_2$	-0.004	(0.003)
$Y_2 \ast x_3$	-0.031^{**}	(0.015)
$Y_3 \ast x_1$	0.011	(0.008)
$Y_3 \ast x_2$	-0.014^{***}	(0.003)
$Y_3 \ast x_3$	-0.004	(0.012)
$Y_4 \ast x_1$	-0.013	(0.013)
$Y_4 \ast x_2$	-0.005	(0.005)
$Y_4 \ast x_3$	-0.028	(0.021)
$Y_2 \ast t$	-0.231^{**}	(0.107)
$Y_3 \ast t$	0.008	(0.096)
$Y_4 \ast t$	0.188^{**}	(0.094)
$x_1 \ast t$	-0.002	(0.075)
$x_2 \ast t$	0.533^{***}	(0.068)
$x_3 \ast t$	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	3504	
N	3855	

* $P < 0.10$.

** $P < 0.05$.

*** $P < 0.01$.

[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 6
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

$^{*}P < 0.10$.

** $P < 0.05$.

*** $P < 0.01$.

management point of view these changes are significant because fishers' ability to control the catch composition suggests that management changes in one fishery may require additional oversight of substitute species [8,25].

The empirical model also controls for red snapper abundance, red snapper license types (Classes 1 and 2), climate variability and season length. The coefficient for stock abundance is, as expected, positive and statistically significant (at 5% level), suggesting that an increase in fish abundance induces an upward shift of the production possibility frontier. This result is consistent with previous research underscoring the importance of accounting for stock abundance [28,29,19], among others. The coefficient for the Class 2 license type (200 lb trip limit) is negative and statistically significant at the 1% level indicating that those vessels that held these licenses were less productive than their counterparts. Climate variability coefficient was not found to be statistically significant which may be explained by two factors.[6] First, red snapper inhabits waters from 30 to 200 ft deep, which tend to have stable temperature conditions. Moreover, [54] shows that sea surface temperatures have been fairly stable since the mid-1990s. 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 [55]. Karnauskas et al. [54] also highlights the difficulties in evaluating the effects of climate and weather variability on commercial fishing operations. Finally, the fishing season length variable was found to be positive and statistically significant at the 1% level suggesting that the added flexibility to fish year-round can yield significant productivity gains. Specifically, the partial elasticity for the open fishing season variable equals 0.09.

6.2. *Changes in total factor productivity and its components*

Table 7 presents TFP changes over the studied period. The reported estimates represent the change in the MI between two consecutive years. Ratios greater than unity indicate an improvement in productivity, meaning that more yield was obtained 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 million pounds in 2006 to 2.99 million pounds (about 30% drop) in 2007 and then dropped again to 2.30 million pounds. in 2008 (another 23%).[7] To offset the impact of the reduced quota, the fleet, on average, prolonged their fishing trips and diversified their landings [24]. Table 3 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%.

Table 7 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 afterwards productivity began increasing at an annual rate of 4.1%.

Table 7
Evolution of total factor productivity 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[a]	0.930	0.960	0.875	–
Post-IFQ[a]	1.041	1.027	–	1.212

[a] Weighted average (by number of vessels).

Table 7 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 retired fleet experienced higher productivity declines (12.5% vs. 4%). Post-IFQ the productivity of the remnant fleet rose from −4% to 2.7%. Table 7 also reports that newcomer fleet was extremely productive reporting annual productivity gains on 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 had been common in the western Gulf [24]. Eastern Gulf catches only recently increased owing to the eastward expansion of the red snapper stock along the West Florida shelf (Table 8).

With respect to the sources of TFP change, Table 9 shows that post-IFQ productivity gains were mostly attributable to changes in technical efficiency rather than from technological progress or changes in stock size. Sexennial pre- and post-IFQ averages 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 9). Finally, Fig. 4 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 lb of red snapper trip limit).

7. Conclusions

This paper investigated the impact of the GOM red snapper IFQ program on the productivity of the vertical line commercial fleet.

Table 8
Average technical efficiency (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

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[6] In preliminary analysis three alternative climatic indicators were tested: (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 the ML function.

[7] Quotas are based on gutted weight.

Table 9
Geometric means of Malmquist Index and its components.

Period	Malmquist Index (MI)	Efficiency change (EC)	Technical change (TC)	Stock change (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[a]	0.930	0.937	0.992	1.000
Post-IFQ[a]	1.041	1.034	1.002	1.005

[a] Weighted average (by number of vessels).

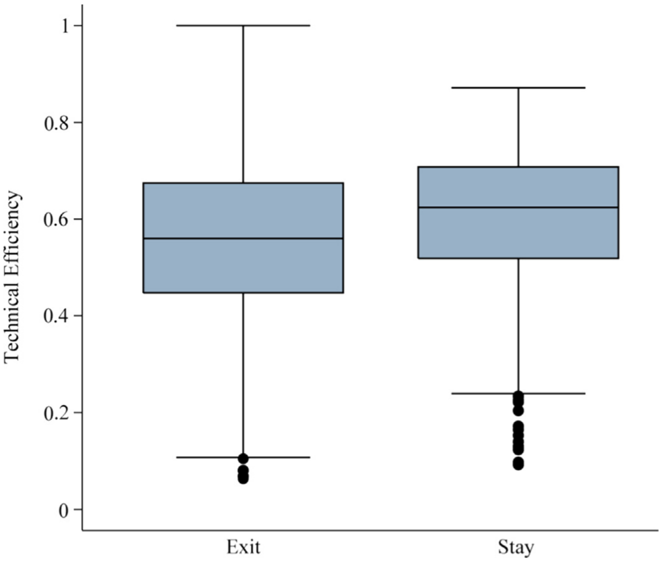

Fig. 4. Distribution of pre-IFQ technical efficiency scores for the retired and remnant fleets (2001–06).

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 of the added flexibility afforded by the program which influenced both extensive and intensive margins. Changes in the extensive margin came about by releasing redundant capital and labor whereas changes in the intensive margin came about by easing regulatory constraints such as trip limits and fishing seasons.

In light of these results and earlier work by [25] suggesting that the current fleet is oversized, regulators interested in spurring productivity gains may want to consider short-run policies that remove surplus capital and labor rather than those that provide research and development opportunities to foster technological improvement and/or enhance fishing skill. Once harvesting capacity becomes more closely aligned with the reproductive potential of the stock, regulators may want to revisit policies that support research and development. However, productivity gains from common-pool resources cannot be sustained indefinitely because quotas are based on conservative exploitation levels to protect the finite reproductive potential of the stock. Finally, while this study focuses on a single IFQ program, these results in combination with the findings from national productivity reviews [30,17] suggest that regulatory changes, especially those in the form of rights or privilege-based management regimes can help boost productivity in the short-run.

Acknowledgements

We would like to thank Alex Chester, Eric Thunberg, John Walden, Walter Keithly, two anonymous referees and the participants in the IIFET and SAEA annual meetings for their useful comments and suggestions. We also indebted to Jakok Tetzlaff and Shannon Cass-Calay for kindly providing red snapper biomass data. The support of NOAA's Office of Science and Technology and FAMU's FRAP program is gratefully acknowledged. The views and opinions expressed or implied in this article are those of the authors and do not necessarily reflect the position of the national marine Fisheries Service, NOAA.

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