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Diversification, efficiency and productivity in catch share fisheries

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ABSTRACT

This study investigates the relationship between diversification, technical efficiency (TE), and productivity in the US Gulf of Mexico commercial red snapper fishery. We estimated a vessel-level input-oriented stochastic distance frontier simultaneously with a technical inefficiency effects model using a 20-year unbalanced panel (1997–2016). The panel documented the fishing activities of 1,255 fishing vessels, 10 years before and after the adoption of the red snapper catch share program in 2007. Our study points to the desirability of diversification in catch share fisheries. It shows that red snapper fishers who diversified their fishing portfolio tended to be more productive and technically efficient. The study found evidence that diversification resulted in cost savings from catching multiple species (diversification economies), and that the productivity of the fleet increased (diversification efficiencies). The analysis also showed that the TE of the fleet increased in the catch share period. The average TE rose from 0.78 in the command and control period to 0.85 in the catch share period. Higher TE scores were associated with higher levels of diversification. Our results suggest that policies that encourage diversification such as reducing quota ownership caps, adjusting quota carryover provisions, and providing governmental assistance to increase participation in other fisheries deserve further attention.

1. Introduction

In the past decade, there has been a renewed interest in investigating the impact of catch (output) diversification in commercial fisheries (Kasperski and Holland, 2013; Sethi et al., 2014; Finkbeiner, 2015; Hentati-Sundberg et al., 2015; Anderson et al., 2017; Cline et al., 2017; Holland et al., 2017; Ward et al., 2018). Most of these studies report that catch (species) portfolios have become more specialized (less diversified), raising concern about fishers' ability to withstand large revenue fluctuations because of declining catches of one or more species. Besides spreading financial risk and reducing livelihood vulnerability, output diversification has also been shown to increase resilience to market and oceanographic shifts (Sethi et al., 2014; Cline et al., 2017). Table 1 presents a summary of recent literature dealing with catch diversification in fisheries.[1]

Although established management approaches such as limited entry were expected to lock fishers into specific fisheries, modern management approaches–which assign exclusive, tradable fishing privileges–such as catch shares, have also reduced diversification despite the flexibility to participate in multiple fisheries by purchasing and/or leasing harvesting privileges (Holland and Kasperski, 2016). Holland et al. (2017) report that while some of the diversification decreases seen in US catch share programs were associated with pre-existing trends, most programs experienced further reductions resulting from consolidation.[2] Holland and Kasperski (2016) argue that the added harvesting flexibility and stability afforded by catch shares may ameliorate some of the negative impacts of catch specialization. In addition, they suggest that there may be a tradeoff between the efficiency gains from specialization and the risk-reduction benefits from diversification.

Few studies have investigated the relationship between diversification, technical efficiency (TE), and productivity of commercial fishing fleets, let alone those under catch shares. Research on agricultural

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[1] Catch (output) diversification can take place at various time frames. In the short-run, fishers can target multiple species within a fishing trip (thus, not requiring different permits, gear, etc.) whereas in the medium- and long-term, fishers can participate in various single and multispecies fisheries say within a fishing season or year (requiring different permits, gear, etc.). In this paper, we aggregated trip level landings into fishing season landings to examine the impacts of catch diversification.

[2] Huang et al. (2018) caution that the trend towards specialization may be confounded in some instances. The authors found that following the introduction of catch shares in the US Northeast groundfish fishery the trawl fleet began diversifying their catch composition while the gillnet fleet did not adjust their catch mix.

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Table 1
Recent studies dealing with diversification in fisheries.

Author(s) (Year of Pub.)	Fishery (Region, Country)	Method	Period of Analysis
Álvarez et al. (2020)	Mixed, small-scale (Gran Canaria, Spain)	Stochastic Production Frontier	2005–2010
Anderson et al. (2017)	Mixed (Alaska, USA)	Hierarchical Bayesian variance function regression model	1985–2014
Cline et al. (2017)	Mixed (Alaska, USA)	Multivariate time series analysis	1980–1999
Finkbeiner (2015)	Mixed, small-scale (Baja California Sur, Mexico)	Diversification index, Linear regression	1997–2008
Holland et al. (2017)	Mixed (USA)	Linear regression	1993–2014
Huang et al. (2018)	Groundfish Fishery (New England, USA)	Stochastic Production Frontier	2007–2012
Kasperski and Holland (2013)	Mixed (West Coast and Alaska, USA)	Gross income diversification index	1981–2010
Sethi et al. (2014)	Mixed (Alaska, USA)	Descriptive statistics	1980–2010
Ward et al. (2018)	Salmon (Alaska, USA)	Revenue function, Bayesian regression model	1975–2016

systems has shown that the relationship between crop diversification and farm productivity and TE is mixed (Rahman, 2009). Understanding TE and productivity changes can valuable because it provides insight into the efficient use of inputs and output growth. This study seeks to contribute to the production literature by examining the impact of diversification on TE and productivity using the US Gulf of Mexico red snapper catch share fishery as a case study. To achieve this goal, we implement an input-oriented stochastic distance frontier (ISDF) simultaneously with a technical inefficiency effects model for an unbalanced panel of 1,255 individual vessels. The data used covers a time-span of 20 years, 10 years before and after the adoption of the red snapper catch share program in 2007.

The rest of this paper is structured as follows. The next section introduces the management history of the fishery, followed by a description of the methods, data and empirical model. Then, we present and discuss the main results. The article concludes with a summary of the main findings and outlines policy implications.

2. The red snapper fishery of the US Gulf of Mexico

The red snapper (*Lutjanus campechanus*) is one the main species of the Gulf of Mexico reef fish complex. The red snapper stock is prosecuted by commercial and recreational interests. Vertical lines and, to a lesser degree, bottom longlines are the main commercial gears that operate in the fishery. Vertical lines catch in excess of 95 % of the red snapper. Red snapper is jointly caught with other species such as vermilion snapper, red grouper and gag. In 2016, about 422 commercial fishing vessels landed 6.1 million pounds (gutted weight, gw) of red snapper worth $28 million in dockside revenues (SERO, 2018). Most of the red snapper are landed on the west coast of Florida, Texas and Louisiana.

The red snapper fishery has a complex management history (Waters, 2001; Keithly, 2001; Porch et al., 2007; Hood et al., 2007; Agar et al., 2014). Its recent federal management history can be divided into two distinct periods: a command and control period (1984–2006) and an individual fishing quota (IFQ) or catch share period (2007-onwards). For ease, we use the terms IFQ and catch share interchangeably. Supplementary Table 1 shows the chronology of the main management actions (SERO, 2018).

The command and control era (1984–2006), began with the adoption of the Gulf of Mexico Reef Fish Fishery Management Plan (FMP) in 1984. The FMP sought to attain the greatest overall benefit to the US by increasing the yield of the reef fish fishery, minimizing user conflicts in nearshore waters and protecting juvenile reef fish and their habitats (Waters, 2001). Initially, the Gulf of Mexico Fishery Management Council (Council hereafter), body that develops management recommendations for the US federal fisheries in the Gulf of Mexico, used minimum size limits and quotas to protect the red snapper resource, but these measures failed. Subsequent stock assessments concluded that the stock was in worse condition than expected, which resulted in reduced commercial quotas, a moratorium on the issuance of new reef fish permits, and red snapper daily trip limit endorsements of 200 or 2000 lb. depending on the vessel's catch history.

Despite these efforts, fishing derby conditions developed and quotas began to be filled progressively sooner. Subsequently, the Council sought to extend the fishing season by splitting the quota into two seasons (spring and fall) and establishing 10/15-day fishing mini-seasons. Waters (2001) reports that these management measures were not only biologically ineffective because of quota overages and high discard rates, but also were economically wasteful because they resulted in overcapacity (i.e., excessive capital investments), short fishing seasons, market gluts, depressed prices, higher harvesting costs, and unsafe fishing practices.

The catch share era (2007-present) began when the Council implemented Amendment 26 on January 1, 2007, which introduced the red snapper IFQ program. The intent of the program was to reduce overcapacity and to eliminate, to the extent possible, the problems associated with derby fishing in the commercial fishery. Under the catch share program, eligible participants were assigned exclusive, tradeable harvesting privileges. A 5-year review of the IFQ program concluded that the program had mixed success reducing overcapacity but was successful in mitigating derby fishing behavior and preventing quota overages. This review noted that the fishing season increased from an average of 109 days to a year-round season. In addition to adjusting the timing of fishing activities, the program also influenced their pace and scope. Fishers began making fewer but longer trips. The average duration of a fishing trip increased from three days in the command and control period to four days in the catch share period because of the elimination of trip limits, fishing windows, and seasonal quotas (Table 2). This added flexibility encouraged a more efficient scale of operation. Red snapper fishers not only increased their landings but also adjusted their catch composition. The vertical line fleet began catching more vermilion snapper and shallow-water grouper species (Fig. 1). Fig. 1 also shows how revenue diversification (proxied by the Herfindahl–Hirschman Index, HHI[3]) evolved over time. Low HHI scores indicate high levels of diversification whereas high HHI scores denote increased specialization (or low levels of diversification). Fig.2 shows that during the catch share period, severe quota cutbacks at the start of the program encouraged revenue diversification (low HHI scores); however, as the stock recovered and quotas rose, revenue diversification decreased (high HHI scores), especially in 2015. Figs. 1 and 2 show that the adoption of catch shares and changing red snapper quota levels may have influenced diversification levels. However, these do not necessarily imply causation. Rising share and allocation (quota rental) prices suggest that the catch share program helped improve economic efficiency in the fishery (SERO, 2018). Capacity studies suggested that about one-fifth of the current fleet could harvest the current commercial quota.

3. Methods

We use a stochastic distance frontier (SDF) model to assess the

[3] More detail about the HHI index is presented in Section 3.2.

Table 2
Descriptive statistics at the trip level.

Variable[a]	Unit	Parameter	Entire Sample (1997–2016) Mean	Entire Sample (1997–2016) S.D.	Pre-Catch Shares (1997–2006) Mean	Pre-Catch Shares (1997–2006) S.D.	Catch Shares (2007–2016) Mean	Catch Shares (2007–2016) S.D.
Red snapper landings	lb /trip	y_1	679.74	1,337.11	557.16	795.54	911.56	1,972.33
Vermillion snapper landings	lb/trip	y_2	297.18	791.03	228.35	670.77	427.36	965.55
Shallow-water grouper landings	lb/trip	y_3	326.38	653.17	278.53	609.73	416.87	719.63
Other snappers landings	lb/trip	y_4	15.92	113.57	12.09	76.49	23.16	161.70
Miscellaneous species landings	lb/trip	y_5	270.30	730.63	249.50	715.34	309.64	757.14
Days away	days	x_1	3.35	2.71	2.97	2.46	4.06	2.99
Crew size	count	x_2	2.80	1.29	2.85	1.34	2.72	1.19
Vessel length	feet	x_3	39.13	10.53	40.02	11.09	37.43	9.14
Log red snapper stock	biomass	$Stock_{RS}$	10.98	0.19	10.86	0.02	11.20	0.17
Log vermillion snapper stock	biomass	$Stock_{VS}$	9.20	0.07	9.17	0.04	9.27	0.07
Diversification score	–	*HHI*	6,982.32	2,428.89	7,156.06	2,344.79	6,653.74	2,548.32
Dominance score	–	*BP*	0.83	0.18	0.86	0.17	0.79	0.20
Red snapper quota	1,000 lb	Quota	4,122	1,059	4,189	0	4,056	1,539
South Texas	dummy	Area A	0.02	–	0.02	–	0.01	–
North Texas	dummy	Area B	0.11	–	0.13	–	0.08	–
Louisiana	dummy	Area C	0.22	–	0.27	–	0.11	–
Alabama-Mississippi	dummy	Area D	0.08	–	0.07	–	0.10	–
North Florida	dummy	Area E	0.37	–	0.34	–	0.43	–
West-Central Florida	dummy	Area F	0.16	–	0.13	–	0.22	–
South Florida	dummy	Area G	0.04	–	0.03	–	0.06	–
N. Observations			*110,545*		*72,310*		*38,235*	

[a] Landings and quota are reported in gutted weight (gw).

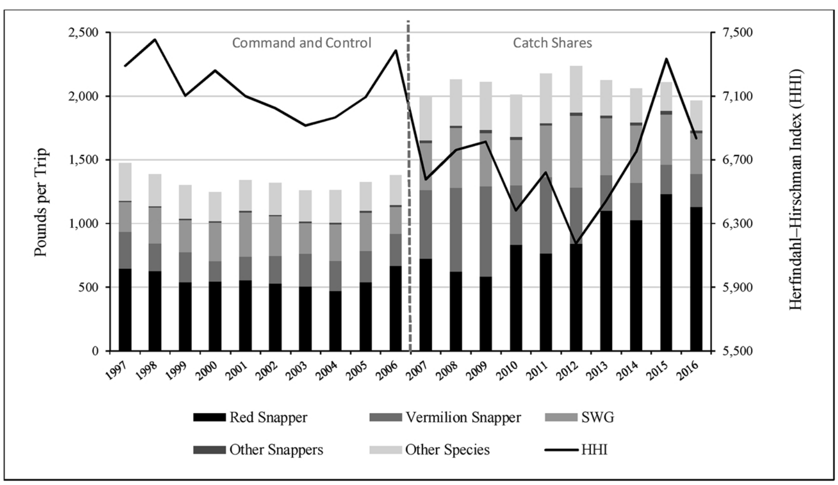

Fig. 1. Evolution of catch shares per trip and diversification index.

impact of output diversification on the performance of the US Gulf of Mexico commercial red snapper fishery.[4] The SDF method was selected because it can accommodate multiple outputs and inputs and can also readily evaluate variables affecting TE (Wree et al., 2018; Solís et al., 2015b; Kumbhakar and Lovell, 2000).

SDFs can have an input- or output-orientation. Our empirical analysis relies on an input-orientation because it can directly measure the effect of diversification on the productivity and efficiency of the fleet. The input orientation assesses the proportional reduction in all inputs that would bring a fishing vessel to the efficient (or best practice) frontier (Kumbhakar et al., 2007). This method relies on a cost minimization framework,[5] which is a plausible behavioral assumption, because catch share programs permit fishers to freely choose the optimal input combination as to maximize their harvesting efficiency and profits.

We define the harvesting technology of fishing vessels using an input set, *L(y)*, which represents the input vector, *x*, which can produce the output vector, *y*. The input-oriented distance function (IDF) is defined on the input set, *L(y)*, is given by:

$$D^I(x, y) = \max\{\lambda: (x/\lambda)\varepsilon L_x(y)\} \quad (1)$$

where D^I is the input distance function, and λ is the efficiency score (Coelli and Perelman, 1999). D^I is non-decreasing, positively linearly

[4] The SDF method is based on an econometric (parametric) specification of a production frontier. A production frontier defines the technological relationship between the level of inputs and the resulting level of outputs from the best performing firms in an industry. In recent years, this method has grown not only in popularity, but also in sophistication. Quang Van (2019) presents a through literature review focusing on marine and fishing industries. Two reviewers pointed out that the usefulness of this method may be limited in fishery research because of the potential of confounding effects brought about changes in institutional arrangements and biological conditions (see Reimer et al., 2017). However, a recent paper by Chávez Estrada et al. (2018) shows that the use of flexible econometric models, such as SDF, addresses most of the criticisms raised by the above paper.

[5] Kumbhakar et al. (2007) show the theoretical basis to derive the ISDF within a cost minimization framework.

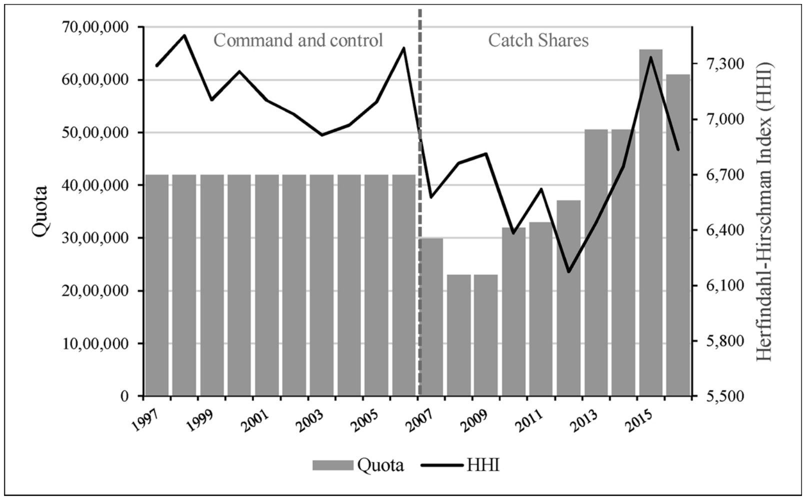

Fig. 2. Evolution of red snapper quota and diversification index.

homogenous, and concave in x, and increasing in y. The distance function, D^I, is equal to unity if the x is located on the inner boundary of the input set.

3.1. Diversification economies

The benefits of diversification can be assessed by examining whether the technology exhibits economies of scope, that is, the cost savings from producing multiple outputs rather than producing them separately. However, because its estimation requires cost data, which were unavailable for the entire study period, we calculated an analogous metric known as diversification economies (DE). DEs measure the gain or loss in total output achievable from the reallocation of inputs among different products (Wree et al., 2018; Solís et al., 2009; Coelli and Fleming, 2004). DEs do not require cost data and can be derived from the parameter estimates of the IDF.

If a *translog* functional form is used to econometrically estimate the IDF (additional detail is offered in the empirical model section) then DEs between output (Y) pairs i and j can be estimated as the second order partial derivative of the IDF function with respect to Y_i and Y_j or $DE_{Y_iY_j} = \frac{\partial^2 IDF}{\partial Y_i \partial Y_j}$ (Morrison Paul et al., 2000).

The second cross partial derivative must be positive to provide evidence of DEs because the first derivative with respect to Y_i is negative (Coelli and Fleming, 2004). The first derivative with respect to Y_i is negative because it captures how the addition of an extra unit of Y_i, holding all the other variables constant, reduces the amount by which we need to deflate the input vector to place the observation onto the efficient (best practice) frontier. Coelli and Fleming (2004) also point out, that in contrast to economies of scope, which allow the output composition to vary to minimize costs, DEs holds them fixed. Hence, DEs can be thought as a lower-bound measure of the economies of scope derived from a cost function.

3.2. Factors affecting technical efficiency

In addition to examining DEs, we investigated what factors influenced the efficiency of the vessels relative to the best practice frontier, focusing on the management regime (command and control vs. catch shares) and fishing practices (alternative diversification metrics). TE vessels produce the maximum catch possible with the minimum amount of inputs. TE vessels operate on the best practice frontier whereas TE inefficient vessels operate inside the frontier because potential catches are forgone due to inefficient input use. We selected the introduction of the catch share program because the program resulted in an extended fishing season and increased regulatory flexibility (i.e., elimination of trip limits, seasonal quotas, fishing windows; Agar et al., 2014). Solís et al. (2015b) also documented improvements in TE and productivity in the catch share period.

We also considered how changes in fishing practices, in particular diversification, affected TE. Table 2 and Fig. 1 show that, after the catch share program, vertical line vessels took fewer, but longer fishing trips and diversified the composition of their catch. We used the HHI and Berger-Parker (BP) indices to explore diversification efficiencies. HHI scores were calculated as $HHI = \sum_{i=1}^{N} s_i^2$, where s_i is the gross revenue share of species i. HHI scores range from close to zero (full diversification) to 10,000 (full specialization). BP is a dominance score, which measures the proportional importance of the most valuable species (Magurran, 1988). BP scores were calculated as $= N_{max}/N$, where N is the total revenue and N_{max} is the revenue from the most valuable species. BP scores range from close to zero to unity.

4. Data and empirical model

4.1. Data

We employed three databases: 1) Southeast Coastal Fisheries Logbook; 2) Permits Information Management Systems (PIMS); and 3) Seafood dealer reports. The logbook database contains information on outputs and inputs (landings and fishing effort), the PIMS database contains information on fishing vessel characteristics, and the dealer database contains data on dockside prices.[6]

Our study focused on how the red snapper vertical line vessels diversified their annual fishing revenue by targeting different species within the Gulf of Mexico region. The analysis included both red snapper and non-red snapper trips. Red snapper is jointly caught with other (catch share and non-catch share) reef fish species. To harvest red snapper (and other reef fish species) fishers are required to have a valid Gulf of Mexico reef fish permit and allocation (quota rental). The vast majority of the red snapper fishers operate mainly in the reef fishery. A small percentage of the vertical line fleet may switch gears (or use multiple gears) during part of the year; however, our analysis was limited to the vertical line fleet because they land most of the red snapper (over 95 %)[7] and also to avoid heterogeneous production biases in the econometric estimation. Huang et al. (2018) note that production decisions may vary significantly across gears in the face of

[6] More information on these databases can be found at http://www.sefsc.noaa.gov/fisheries.

[7] Thus, focusing on vertical liners should not generate any econometrics issues related to sample selection bias.

the same regulatory change.

After merging the databases, we ended up with a highly unbalanced panel that contained 110,545 trip-level observations on 1,255 distinct fishing vessels. Table 2 presents trip-level summary statistics of the panel. Following Felthoven and Morrison Paul (2004), we aggregated trip-level data to seasonal or quarterly level (January-March, April-June, July-September, and October-December). This aggregation might have affected the strict interpretation of the seasonal HHI scores since two distinct fishing vessels could have an identical ‘seasonal HHI’ score but have different trip-level revenue mix profiles within the season. To control for this situation, we also incorporated the standard deviation of HHI scores (SD HHI), where low SD HHI values imply that trips within the season show a more diversified output mix. BP indices were also aggregated seasonally. The final dataset used in the analysis contained 21,191 (seasonal vessel-level) observations. The analysis covered a 20-year span ranging from 1997 to 2016 (10 years before and after the catch share program).

4.2. Empirical model

An input-oriented stochastic distance frontier (ISDF) was employed to estimate the production frontier. Coelli and Perelman (1999) show that a second-degree approximation to a true IDF can be depicted using a *translog* functional form with symmetry and homogeneity imposed:

$$\ln\left(\frac{D_i^I}{x_{1i}}\right) = \alpha_0 + \sum_m^M \alpha_m \ln y_{mi} + 0.5\sum_{m_i}^M \sum_{m_g}^M \alpha_m \ln y_{m_j i} \ln y_{m_g i} + \sum_n^{N-1} \beta_n \ln\left(\frac{x_{ni}}{x_{1i}}\right) + 0.5\sum_{nj}^{N-1}\sum_{ng}^{N-1} \beta_{nn} \ln\left(\frac{x_{nji}}{x_{1i}}\right)\ln\left(\frac{x_{ngi}}{x_{1i}}\right) + \sum_n^{N-1}\sum_m^M \delta_{nm} \ln\left(\frac{x_{ni}}{x_{1i}}\right)\ln y_{mi} + \sum_s^S \omega_s d_s \tag{2}$$

where the subindex i denotes fishing vessel i and d_s characterizes all control variables in the model.

Using the traditional framework of the stochastic production frontier method, we can formulate an ISDF in which the distance from each observation to the ISDF represents the sum of inefficiency and a traditional error term (i.e., $D^I = \varepsilon = \nu$ - u):

$$\ln\left(\frac{D_i^I}{x_{1i}}\right) = \alpha_0 + \sum_m^M \alpha_m \ln y_{mi} + 0.5\sum_{m_i}^M \sum_{m_g}^M \alpha_m \ln y_{m_j i} \ln y_{m_g i} + \sum_n^{N-1} \beta_n \ln\left(\frac{x_{ni}}{x_{1i}}\right) + 0.5\sum_{nj}^{N-1}\sum_{ng}^{N-1} \beta_{nn} \ln\left(\frac{x_{nji}}{x_{1i}}\right)\ln\left(\frac{x_{ngi}}{x_{1i}}\right) + \sum_n^{N-1}\sum_m^M \delta_{nm} \ln\left(\frac{x_{ni}}{x_{1i}}\right)\ln y_{mi} + \sum_s^S \omega_s d_s + +\nu_i - u_i \tag{3}$$

where u_i and ν_i are the elements of the composed error term, ε_i, defined by Aigner et al. (1977). Specifically, ν_i is a random variable reflecting noise and other stochastic shocks, and u_i captures the TE relative to the stochastic frontier.

The specification of the seasonal model included: 1) five outputs: red snapper (y_1), vermillion snapper (y_2), shallow-water groupers (SWG; y_3), other snappers (y_4), and a residual or miscellaneous species group (y_5); 2) two variable inputs including seasonal totals for days at sea (x_1)[8] and crew size (x_2); 3) vessel length (x_3), which controls for fishing capital (quasi-fixed input).[9] In addition, we included a set of biological, environmental, regional and seasonal control variables: spawning biomass index for red and vermillion snapper; multivariate El Niño Southern Oscillation (ENSO) index to account for climate variability; and regional landing dummies to control for regional variability across the Gulf region. Seasonal changes in fishing conditions were controlled using quarterly dummy variables (Q_1, Q_2, Q_3, and Q_4 was the base quarter). Biomass and ENSO trends are presented in Fig. 3.

To increase the flexibility of the model, technical change was modeled using linear and quadratic time trends (t and t^2) and interactions of the time trend with input and output quantities were also introduced to account for non-constant rate changes and for non-neutral technical change.[10] One benefit of this flexible form is that it allow us to measure how elasticities change over time.

Within this framework, the predictor of TE was measured following Jondrow et al. (1982) as the expectation of u_i conditional on the composed error term ε_i:

$$TE = exp(-u_i) \tag{4}$$

TE can be interpreted as a relative measure of managerial ability or fishing skill in our case. Caudill et al. (1995) proposed a framework to analyze the extent to which certain variables influence the inefficiency term u_i. These authors developed a model in which the determinants of inefficiency were evaluated using a multiplicative heteroscedasticity framework. In our analysis, it took the form of:

$$\sigma_{u_i} = \sigma_u \bullet exp(Z_{mi}; \alpha) \tag{5}$$

where Z_{mi} is a vector of management interventions (dichotomous variable for the catch share period) and fishing practices (revenue-diversification, standard deviation of revenue diversification, and revenue dominance, measured by HHI, SD HHI and BP, respectively that explain inefficiency and αs are unknown parameters. Given that inefficiency is assumed to follow a half-normal distribution, decreasing variance measures efficiency gains. Both the ISDF and the inefficiency model are estimated jointly using maximum likelihood.

5. Results and discussion

5.1. Model performance

Parameter estimates of the ISDF are presented in Table 3. Close to 85 % of the estimated parameters were statistically different from zero. All first-order coefficients were statistically significant. The majority of second-order terms were also significant, confirming the presence of non-linearities in the production process, which supports the use of a flexible *translog* functional form.[11] Table 4 shows that our empirical model is non-decreasing in inputs and decreasing in outputs, necessary conditions for a well-behaved ISDF.

Additional hypothesis tests using likelihood ratio tests were also conducted. Table 4 presents the parameter estimate and significance level of $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$, which ranges from zero (absence of technical inefficiency) to unity (absence of random noise; Rahman, 2009). γ was found to be statistically different from zero at the 1 % level. The rejection of the null hypothesis H_o: $\gamma = 0$, implies the existence of a stochastic frontier function. We also rejected the null hypothesis that all slope coefficients in the inefficient model were equal to zero. In addition, we tested for input-output separability by setting all cross-terms between outputs and inputs equal to zero. A likelihood ratio test rejected the presence input-output separability implying that the input and output vectors cannot be aggregated into a single aggregate input and single aggregate output (Jensen, 2002).

[8] x_1 was used to impose linear homogeneity in inputs in our model.

[9] One reviewer argued that, in commercial fishing, all inputs should be treated as quasi-fixed. We agree that vessel length is always quasi-fixed (as in our paper); but disagree that crew size and trip length (fishing time) are always quasi-fixed. In the Gulf of Mexico red snapper fishery, Table 3 shows that in the catch share period, fishers increased the average crew size by 4.6% and the average trip length by 37%. Similar model specifications to ours can be found in Álvarez et al. (2020); Huang et al. (2018); Agar et al. (2017); Solís et al. (2015a, 2015b, 2014, 2013); Pascoe et al. (2012); Felthoven et al. (2009), among others.

[10] Squires and Vestergaard (2020) discuss the implications of technical change on the exploitation of renewable resources.

[11] The generalized likelihood ratio test also rejected the Cobb-Douglas against the *translog* functional form.

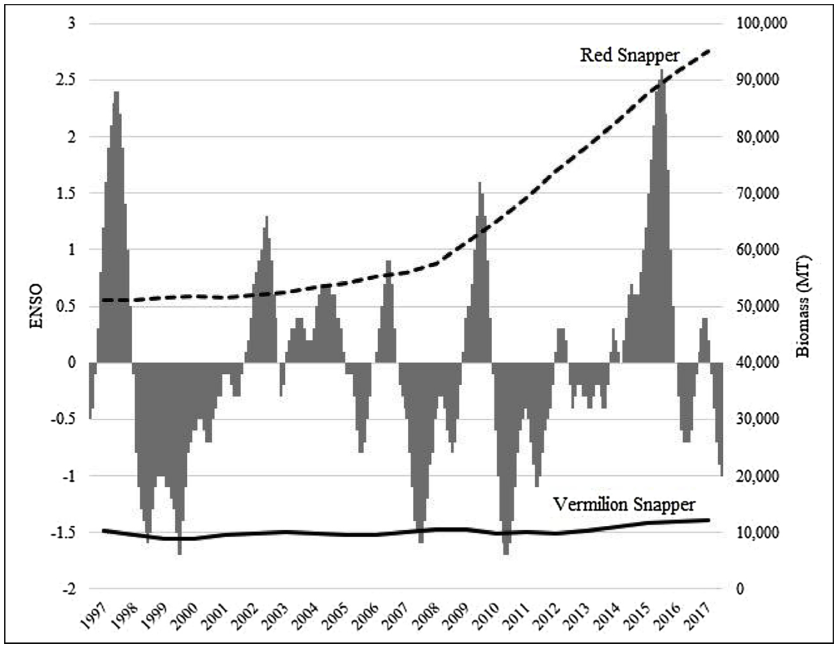

Fig. 3. Evolution of environmental variables: ENSO and biomass.

Table 3
Parameter estimates of the input distance function.

Parameter	Coefficient	SE	Parameter	Coefficient	SE
Constant	1.7821	(1.2746)	*Area B*	−0.0509***	(0.0094)
y_1	−0.0684***	(0.0009)	*Area C*	−0.0686***	(0.0093)
y_2	−0.0540***	(0.0006)	*Area D*	−0.0184*	(0.0099)
y_3	−0.0639***	(0.0010)	*Area E*	−0.0282***	(0.0094)
y_4	−0.0314***	(0.0007)	*Area F*	−0.0661***	(0.0101)
y_5	−0.0620***	(0.0009)	*Area G*	−0.0671***	(0.0112)
$y_1 * y_1$	−0.0119***	(0.0003)	Q_1	−0.0141***	(0.0032)
$y_2 * y_2$	−0.0111***	(0.0003)	Q_2	−0.0136***	(0.0031)
$y_3 * y_3$	−0.0104***	(0.0004)	Q_3	−0.0145***	(0.0032)
$y_4 * y_4$	−0.0027***	(0.0005)	$Stock_{RS}$	−0.1092*	(0.0749)
$y_5 * y_5$	−0.0099***	(0.0004)	$Stock_{VS}$	−0.1447***	(0.0379)
$y_1 * y_2$	0.0004***	(0.0001)	*ENSO*	0.0002	(0.0015)
$y_1 * y_3$	0.0009***	(0.0002)	t	0.0044***	(0.0008)
$y_1 * y_4$	0.0002	(0.0002)	t^2	0.0004	(0.0002)
$y_1 * y_5$	0.0019***	(0.0002)	$x_2 * t$	−0.0011***	(0.0003)
$y_2 * y_3$	0.0012***	(0.0002)	$x_3 * t$	0.0034***	(0.0006)
$y_2 * y_4$	0.0001	(0.0002)	$y_1 * t$	0.0003***	(0.0001)
$y_2 * y_5$	0.0013***	(0.0002)	$y_2 * t$	0.0003***	(0.0001)
$y_3 * y_4$	0.0001	(0.0002)	$y_3 * t$	0.0001	(0.0001)
$y_3 * y_5$	0.0029***	(0.0002)	$y_4 * t$	0.0003***	(0.0001)
$y_4 * y_5$	0.0008***	(0.0002)	$y_5 * t$	0.0006***	(0.0001)
x_2	0.1885***	(0.0025)	**Inefficiency model**		
x_3	0.1365***	(0.0047)	*Constant*	−15.9716***	(1.2192)
$x_2 * x_2$	0.0038	(0.0035)	*HHI*	0.0004***	(0.0001)
$x_3 * x_3$	−0.2120***	(0.0114)	*SD HHI*	3.3932***	(0.3649)
$x_2 * x_3$	0.0321***	(0.0057)	*BP*	9.1502***	(1.4096)
$x_2 * y_1$	0.0039***	(0.0006)	*CS dummy*	−0.7324***	(0.0833)
$x_2 * y_2$	0.0080***	(0.0006)	σ_u	0.0426***	
$x_2 * y_3$	0.0052***	(0.0007)	σ_v	0.1510***	
$x_2 * y_4$	0.0015*	(0.0008)	$\lambda = \sigma_u / \sigma_v$	0.2821***	
$x_2 * y_5$	0.0024***	(0.0008)	$\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$	0.0737***	
$x_3 * y_1$	−0.0088***	(0.0010)	Log-Likelihood	8,568.9886	
$x_3 * y_2$	−0.0155***	(0.0011)	N	21,191	
$x_3 * y_3$	−0.0161***	(0.0013)			
$x_3 * y_4$	−0.0016	(0.0014)			
$x_3 * y_5$	−0.0027*	(0.0014)			

* 10 % level of significance, ** 5 % level of significance, ***1 % level of significance.

Table 4
Partial elasticities and returns to scale.

Elasticities	Whole Sample	Command and control	Catch Shares
Input elasticities			
x_1[a]	0.681***	0.653***	0.720***
x_2	0.183***	0.191***	0.173***
x_3	0.136***	0.156***	0.107***
Output elasticities[b]			
y_1	0.067***	0.070***	0.065***
y_2	0.052***	0.052***	0.053***
y_3	0.063***	0.062***	0.064***
y_4	0.030***	0.029***	0.031***
y_5	0.059***	0.052***	0.064***
RTS[c]	***3.690****	***3.773****	***3.610****

*10 % level of significance, ** 5 % level of significance, ***1 % level of significance. P-values were estimated based on the delta method.

[a] Elasticities for x_1 are computed by homogeneity conditions.

[b] The partial output elasticity corresponds to the negative of its estimate.

[c] The RTS correspond to the inverse of the sum of output elasticities (Coelli and Perelman, 1999).

Table 5
Diversification economies.

Species	Vermillion snapper	SWG	Other snapper	Other species
Red snapper	0.0004***	0.0009***	0.0002	0.0019***
Vermillion snapper		0.0012***	0.0001	0.0013***
SWG			0.0001	0.0029***
Other snappers				0.0008***

*10 % level of significance, ** 5 % level of significance, ***1 % level of significance.

5.2. Characteristics of the technology

Table 5 presents input and output partial distance elasticities and returns to scale (RTS) estimates.[12] These measures were estimated for the whole period and by management regime (i.e., command and control and catch share periods). All the output partial distance elasticities were positive, highly inelastic, and statistically significant. The own output partial distance elasticity of red snapper indicates that to increase red snapper landings by 1 % fishers need to increase the use of all inputs by 0.07 % (holding all input ratios constant). Most output partial distance elasticities in the catch share period rose presumably because catch shares allowed fishers to better use scarce inputs.

RTS were estimated as the inverse of the sum of output partial distance elasticities (Coelli and Perelman, 1999). Table 4 shows that the RTS for the entire period equaled 3.69, indicating increasing RTS. Estimates of increasing RTS for the harvesting sector have been reported in Bjørndal and Gordon (2000); Felthoven et al. (2009) and Solís et al. (2014). Previous research has suggested that increasing RTS arises from substantial overcapacity in the fishery (Asche et al., 2009). Our results show a 4.3 % decrease in RTS during the catch share period (from 3.77 to 3.61), implying a drop in overcapacity. Solís et al. (2014) and Ropicki et al. (2018) have argued that the RTS declined because the less efficient vessels left the fishery and harvest restrictions eased.

Our model also included several control variables (e.g., fish abundance, climate variability, fishing regions (landing regions) and fishing seasons). Rasmussen (2010) explains that, in an ISDF framework, if the coefficient of a control variable is positive (negative) then the fishing firm faces higher (lower) production costs. As expected, fish abundance estimates for red and vermillion snapper were negative indicating that high fish abundances lower harvesting costs.

The ENSO parameter estimate, which captured the effect of climate variability on production, was not statistically significant.[13] Solís et al. (2015b) also did not find statistically significant results on the impact of climate variability on the Gulf of Mexico red snapper fishery. Karnauskas et al. (2015) report that, since the mid-1990s, the sea surface temperatures in the US Gulf of Mexico have been stable, and discuss the difficulties assessing the impact of climate and weather on fishing.

All regional dummies displayed statistically significant coefficients. Fishing vessels operating off the coast of Louisiana were found to be the most productive, while those operating off the coast of Alabama and Mississippi were found to be the least productive.

Following Kumbhakar et al. (2013) we calculated the rate of technical change (TC) as TC = $\partial \ln D_i / \partial t$. Annual TC rates for the entire, command and control, and catch share periods equaled 0.265 %, 0.196 %, and 0.395 %, respectively. These results imply an overall positive, but small, trend in TC over the study period. Our results also show that catch shares encouraged TC.

5.3. Impact of catch diversification on the performance of the fishery

Coelli and Fleming (2004) and Wree et al. (2018) explain that DEs measure the impact of diversification on the shape of the production technology (production structure), and consequently, on the productivity of the fleet. Table 5 shows that all ten DEs are positive, and that seven of those are statistically significant, indicating that we cannot reject the null hypothesis of no DEs at conventional significance levels.[14]

The highest diversification gains were found in the [SWG - Other Species] pair, followed by [Red Snapper - Other Species] pair and [Vermillion Snapper - Other Species] pair (Table 5). DE values are small in magnitude. However, Coelli and Fleming (2004) clarify that these are lower-bound estimates of scope economies. Comparable low-value DE estimates have been reported in agricultural settings (e.g., Wree et al., 2018; Solís et al., 2009; Coelli and Fleming, 2004). Squires et al. (1998) note that species overlap in time and space bound the extent of the economies of scope in commercial fisheries.

The lower panel of Table 3 presents the parameter estimates of the inefficiency model. Following common practice, we interpret the impact of these variables relative to TE (rather than to TI), which means that the estimated coefficients should be interpreted as if they had the opposite sign. Table 3 shows that TE of the fleet increased during the catch share period.

Parameter estimates for revenue diversity, standard deviation of revenue diversity, and revenue dominance (HHI, SD HHI and BP) were negative and statistically significant, suggesting that diversification (low HHI, SD HHI and BP scores) and TE were positively associated. These results imply that, all other things being equal, vessels that diversify their landings tend to be more efficient.

Mean TE scores were calculated for the entire and by management regime (command and control, and catch share). The average TE score for the entire period equaled 0.80, indicating substantial levels of inefficiency. When we split TE scores by management regime we observe that the TE of the fleet increased following the adoption of the catch share program. Mean TE scores rose by nearly 9 % from 0.78 to 0.85. Similar outcomes have been reported by Brandt (2007);, Pascoe et al. (2012) and Solís et al. (2014). These authors proposed that TE improvements could be partly explained by the exit of the less efficient vessels. In addition, the TE of the red snapper fleet possibly improved during the catch share period because many of the former Class 1 vessels (2,000 lb trip limit) who received a sizable share of the initial quota allocation, began to diversify their landing since they were no longer constrained by trip limits, short seasons, and seasonal quotas. Solís et al. (2015b) found that Class 1 vessels (2,000 lb trip limit) were more productive than Class 2 vessels (200 lb trip limit). While it may be tempting to suggest that the reported TE increases occurred because of the catch share program; these do not imply causation. Additional work is necessary to isolate the impact of catch shares on TE and productivity.

Fig. 4 shows the Kernel density distribution of TE by diversification terciles (high, medium and low). This figure shows that the distribution of TE scores for the most diversified vessels is significantly higher and narrower than for those with medium and lower levels of diversification. When we split TE scores by the upper and lower diversification terciles within each management regime, we observe again that diversification is associated with higher levels of TE (Fig. 5). In both cases, the distribution of TE scores became steeper and narrower during the catch share period (Fig. 5). A similar outcome is reported by Álvarez et al. (2020), who found that catch diversification is associated with higher TE levels among small-scale fishers in the Spanish island of Gran Canaria.

Fig. 6 shows the evolution of mean TE and HHI scores over time. It shows a positive association between TE and diversification. This figure also shows that generally TE and diversification rose during the catch share period except for 2015 when there was abrupt and significant red snapper quota increase (23 %). Fig. 6 also shows that the fleet becomes more homogenous during the catch share period, which is captured by the size of the circles. The size of the circles is proportional to the annual coefficient of variation of the TE scores.

[12] A Wald-type test was used to test the significance of all elasticities and RTS and p-values are based on the delta method. All partial input and output elasticities and RTS are statistically significant at a 1% level.

[13] Similar results were found in preliminary analysis testing alternative climatic indicators including: the annual and seasonal average sea surface temperature (SST); the Japan Meteorological Agency (JMA) ENSO index; and, the accumulated cyclone energy (ACE).

[14] A likelihood ratio test against a restricted model making all DEs equal to zero confirms this result.

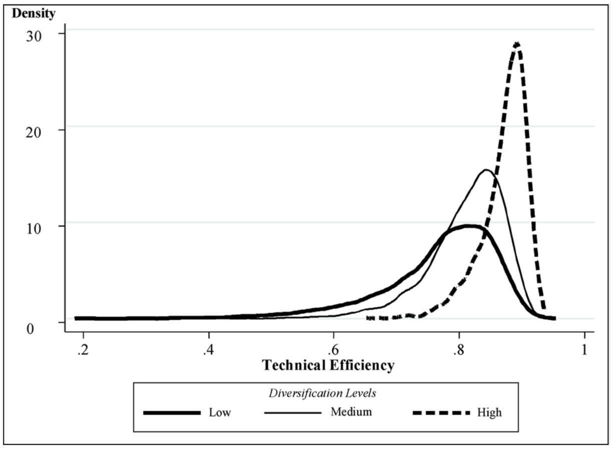

Fig. 4. Kernel density distribution of TE for vessels with low, medium, and high diversification levels.

6. Concluding remarks

Diversification is recognized as a desirable livelihood strategy because it increases fishers' opportunities and income, and reduces income fluctuations caused by shifts in fish abundance, market and oceanographic conditions as well as regulatory actions. Recent work showed that many US catch share fisheries have become less diversified (specialized) suggesting that there may be a tradeoff between the efficiency gains from specialization and risk-reduction benefits from diversification.

Our study points to the desirability of diversification in catch share fisheries. It shows that red snapper fishers who diversify their fishing portfolio tend to be more productive and technically efficient. Without being prescriptive, our work suggests that policies that encourage diversification deserve further attention. One possibility would be to establish share and allocation (accumulation) caps that make red snapper quota more available. In common with other catch share fisheries, red snapper quota ownership has become concentrated and expensive; thus, revising ownership caps could provide additional opportunities to re-enter the fishery and/or to readjust fishing portfolios. Similarly, added flexibility to carryover unused quota into the future (or borrow quota from the future) could also increase quota availability and foster diversification. Additionally, government agencies should consider providing economic assistance (e.g., low-interest loans, grants, or other subsidies) to facilitate the purchase or lease of quota.

All the above policy proposals, in addition to increasing diversification opportunities, have the potential to make quota more affordable to small participants and new entrants as well as reducing discarding. In the eastern Gulf, many red grouper fishers frequently discard incidentally caught red snapper because of the high cost of allocation (Cullis-Suzuki et al., 2012; Agar et al., 2014). Government assistance could also be used to enter (or increase participation in) non-reef fish fisheries, which would increase fishers' resilience to biomass, market and oceanographic shifts since most of the vertical line fleet primarily operates in the reef fish fishery.

CRediT authorship contribution statement

Daniel Solís: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Juan J. Agar:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Supervision, Writing - original draft, Writing - review & editing. **Julio del Corral:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

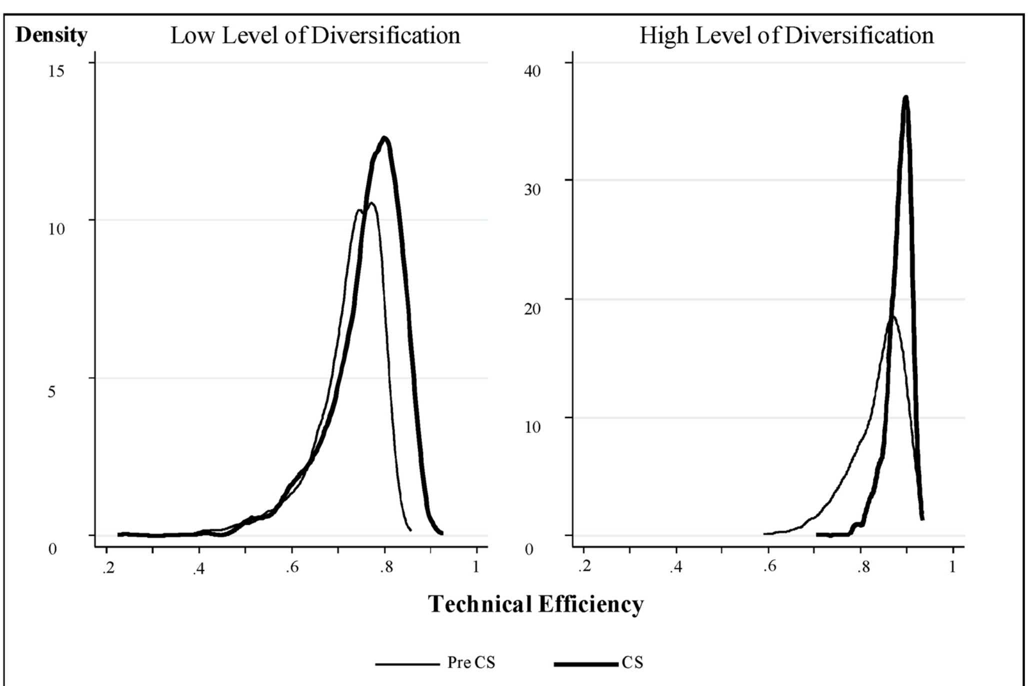

Fig. 5. Kernel density distribution of TE for vessels with low and high levels of diversification before and after the implementation of the catch shares program.

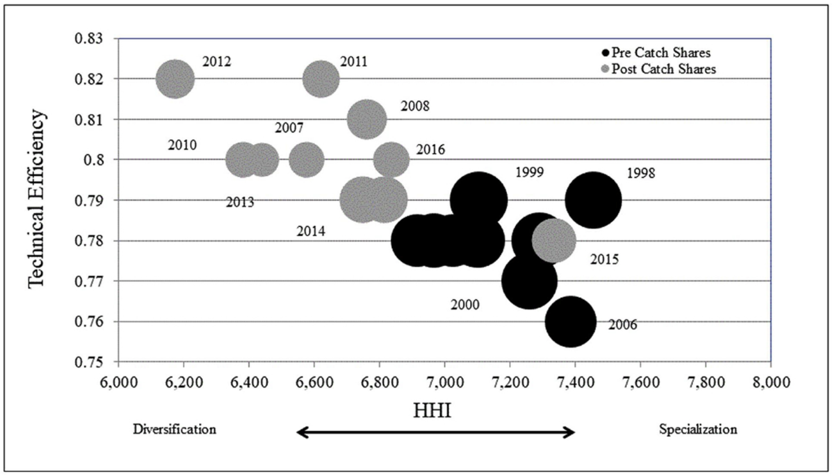

Fig. 6. Relationship between diversification levels and TE scores: Annual averages before and after the implementation of the catch shares program.
Note: Circle sizes are proportional to the coefficient of variation of the annual TE scores.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.fishres.2020.105532.

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